OPTIMIZING FORECASTING METHODS FOR INTERMITTENT USTRANSCOM RAILCAR DEMANDS

THESIS

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Abstract

The United States military heavily relies on rail freight operations to meet many of its logistical needs during both peacetime and wartime efforts. As the head organization responsible for managing and overseeing all modes of military transportation, United States Transportation Command depends on timely accurate railcar demand forecasts to drive critical decisions on distribution and placement of railcar assets. However, the intermittent nature of railcar demands based on location and commodity make it a challenging task for forecasters. Furthermore, these "lumpy" demands often come without any obvious trends or seasonality. This study explores the utility of both traditional forecasting methods and newer techniques designed specifically for handling intermittent demands. All forecasting parameters for each method are optimized based on specific cost functions. Accuracy metrics are then applied to all forecasts for analysis. The results indicate that for the Department of Defense's railcar demands, optimizing basic forecasting methods such as Simple Moving Averages and Simple Exponential Smoothing outperform more popular methods for sparse demands such as Croston's method and its variants. Despite its theoretical superiority, applying Croston's method to railcar demands was found questionable and consistently produced poor forecasts compared to other methods. Analysis provides valuable insight in future strategies for forecasting intermittent demands.

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OPTIMIZING FORECASTING METHODS FOR INTERMITTENT USTRANSCOM RAILCAR DEMANDS

I. Introduction

Background

For years, rail transportation has been one of the most fundamental cornerstones of growth and industry in the United States. The ability to move goods through railways has become one of the most critical assets in transportation. Today, the US rail network is considered one of the most dynamic freight systems in the world. According to the Federal Rail Road Administration, this intricate network accounts for almost 40 percent of all US freight movement by ton-miles [1]. As illustrated in Figure 1, the rail lines transport everything from natural resources and chemicals to automobiles and machinery. The benefits of moving freight by rail include up to four times better cost efficiency compared to trucks, lower greenhouse gas emissions, and a reduction of highway gridlock for timely delivery [2]. The result is an organized group of rail carriers that make up a multimillion dollar industry.

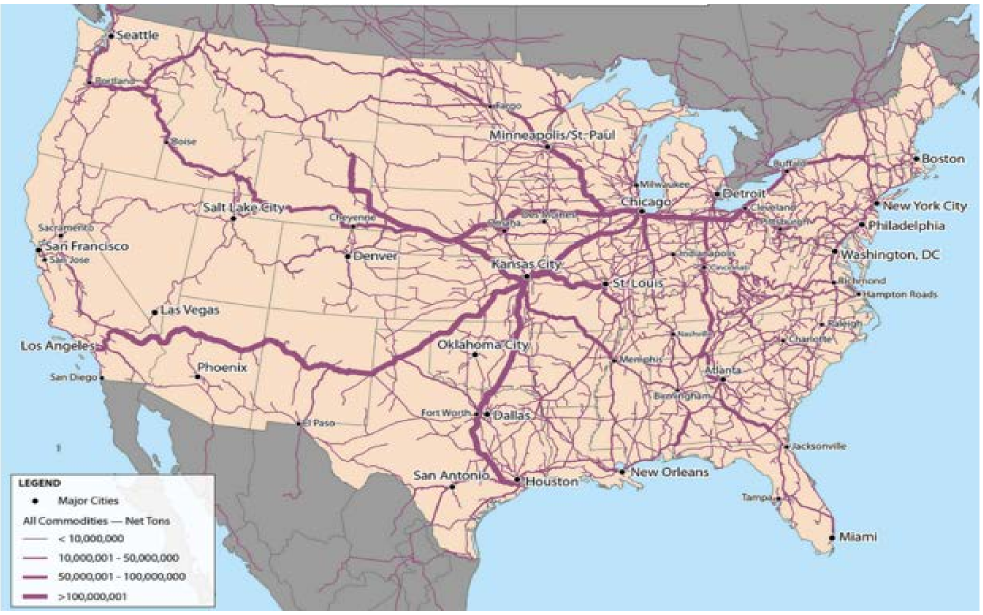


Figure 1 Net Tons for all Commodities [1]

The US military also utilizes this rail network to meet many of its logistical needs. Historically, heavy tanks, trucks, and even rocket engines have been transported between bases using these railways with the use of specialized railcars. Military rail operations occur on a regular basis to fulfill commodity needs and training exercises. However, the railway demands greatly increase during contingency missions and mobilization for deployments.

U.S Transportation Command (USTRANSCOM) is located at Scott Air Force Base, IL and acts as the lead organization responsible for managing and overseeing all modes of military transportation. Within USTRANSCOM, rail movement is split into two methods: commercial and organic. On the commercial side, five major rail carriers Burlington Northern Santa Fe Railway, Chessie and Seaboard System Transportation, Union Pacific, Kansas City Southern Railway, and Norfolk Southern are involved in most of the US rail activity and provide services for military requirements [3]. According to a report, the Army spent about $120 million on rail transportation in 2012 which was about 5% of the entire Army's transportation budget [4]. Most of the money goes towards commercial contracts to operate train activity. Organic railcars are Department of Defense (DoD) owned trains used exclusively for DoD purposes [5]. These organic railcars provide support in case of commercial train stock shortages, extended military operations, or a requirement for increased responsiveness. The synergistic nature of these two methods make the US rail networks an invaluable asset for military logistics.

However, with the possession of such a relevant resource comes the great task of properly planning and managing its use. During Operation Iraqi Freedom, rail transportation played a critical role during wartime but faced a number of problems early on. Despite adequate railcar availability, spot shortages arose along with instances of poor utilization of equipment. Because of time sensitive mission requirements, planners were forced to find expensive alternatives such as motor vehicles [3].

A shortage of demanded railcars results in a cost to back order that specific railcar or depending on the commodity, the high cost of transportation through motor carriers. One must also consider the opportunity cost caused by the delay and failure to move shipments on time. Furthermore, railcars not being used may incur an inventory cost for idly sitting at a hub when they could be used at locations elsewhere. Most of these costs can be broken down into tangible categories but some are intangible. From an operations research perspective, the rail transportation field offers an abundant supply of challenging problems. In a cost constrained environment it is crucial for military planners to have the tools to make these practical decisions.

Problem Statement

Proper planning and placement of specialized railcars is essential to economical rail transportation. USTRANSCOM relies on accurate railcar demand forecasts to drive their decisions regarding distribution and placement of railcar commodities. These forecasts also have major influence in important fleet management procedures and yearly rate setting adjustments. Unfortunately, the irregular and intermittent nature of railcar demand's time series create an extremely challenging task for forecasters at USTRANSCOM. When aggregated by location and railcar commodity types, these "lumpy" demands often come without any obvious trend or pattern causing numerous problems for forecasters. Consequently, current procedures result in impractical forecasts and major inefficiencies.

USTRANSCOM requires an improved process for determining optimal forecasting techniques for intermittent railcar demands and a system to better understand lumpy time series behavior. This study fills that gap and offers insight into the performance and practicality of forecasting techniques that focus primarily on handling sparse time series data. As budgets continue to shrink, the urgency to deliver accurate and timely forecasts for military planners will certainly grow.

Methodology

This study focuses on gaining insight in finding appropriate practices for dealing with highly intermittent time series demand data. First, historical railcar demand data is pulled from USTRANSCOM's database and filtered by location, railcar type, and month used. Data is split into a 3-year initialization/training set from 2011 to 2013 and a 1-year experimentation/validation set in 2014. After the data is organized into a collection of times series data, forecasting methods relevant to lumpy intermittent demands are selected based on the literature search. In addition, specific cost functions are determined for each forecasting method to ensure suitable forecasts. Based on these selected cost functions, all forecasting methods are optimized and applied to the historical rail transport data using commercial statistical software. In the end, all forecast outputs are compared and analyzed across the board using individual accuracy metrics. The problem essentially becomes a maximax function where the top forecasting methods are optimized and ranked.

Assumptions and Limitations

While an abundant amount of transportation data has been provided by USTRANSCOM, there are still critical factors to consider. By nature, the intermittency and irregularity of railcar demand data makes it difficult to track and forecast. This study assumes that the data is accurate and complete with no missing demands or major errors. In addition, the researcher did not implement a rigorous cost dimension to this study. Even though concepts such as over-ordering and holding inventory as considered in the analysis of results chapter, specific costs are not used. Instead, this study emphasizes forecasting techniques and error precision. Another important assumption is that this study does not round forecasts to the nearest whole number. For example, a railcar forecast of 2.88 for a single time period should be rounded up to 3 railcars. However, the intent of this study is more focused on pure accuracy and performance of forecasts. Therefore, forecasts are not rounded up or down. Finally, the time series data is organized by month and did not look into specific weeks or days in time for scope purposes.

Expected Outcomes

In the end, forecasters will not only be able to assess current forecasting techniques, but also see the potential for newer unconventional methods. Improved methods give planners the ability to make better use of historical railcar data leading to improved forecasting results. This research will allow decision makers to gauge the risk in selecting certain methods and give more confidence in ignoring others. Having this level of insight is invaluable for an effective organization. Overall, it will allow managers to deal with intermittent railcar demands and operations more efficiently.

Summary

This research begins with a detailed literature search exploring past works focusing on intermittent demand and the evolution of popular techniques. Next, the forecasting methods suggested in the literature review are formulated and applied to the organized dataset. After optimized forecasts are produced, the results are then examined and analyzed to find the top methods for forecasting railcar demand. Essentially, all selected forecasting methods are manipulated to perform at their highest level leading to the determination of the most practical forecasting approach. Finally, based on the analysis of results, conclusions and recommendations are made. Here, significance and impacts on the problem are explained in order to make meaningful changes to rail freight forecasting policies.

II. Literature Review

Chapter Overview

This chapter provides a working knowledge of the foundations of forecasting intermittent demand and the Department of Defense's relationship with the US railroad network through a comprehensive look at current work in the field. Research in intermittent forecasting has steadily become more popular with numerous applications not only in the military but in the commercial sector as well. The techniques discussed in this chapter have been applied to a multitude of diverse manufacturing and service environments including heavy machinery and spare parts [6] [7] [8] [9]. A review of these works identifies important contributions previously researched and potential areas for research.

First, we will present traditional forecasting methods that have laid the foundation for most of the techniques still implemented and taught today. While some of the more traditional techniques have been found to be inappropriate to forecasting intermittent demand, it is worthwhile to understand their mechanics and how they have evolved to improved methods discussed in this thesis. Forecast accuracy metrics are also discussed to recognize how forecasts are measured and compared.

Next, we review works focusing specifically on forecasting intermittent demand. It is important to first set a solid definition of intermittent lumpy demand and how it's defined by researchers. Then in logical order, advancements to the field are shown to gain fundamental insights and potential areas for further research. Finally, this chapter examines the role DoD and commercial railcar assets play in transportation logistics. In the end, a clearer understanding of demand forecasting's current state is set for the rest of the analysis in this thesis.

Traditional Forecasting Methods

Forecasting plays a critical role in all types of organizations since prediction of future events must be incorporated into decision making processes. As supported by research, inaccurate forecasts surely lead to poor planning and high costs for decision makers. In this sense forecasting lies at the heart of planning. Due to the increasing relevance of forecasting under uncertainty and the value it brings to both commercial and government fields various methods have been proposed over the time. It has become both a science and an art. In order to present the necessary background for comparing specific forecasting methods later, this section of the literature review focuses primarily on familiar moving averages. One piece that covers many of the traditional forecasting methods in use today is Archer's, "Forecasting Demand." The author classifies forecasting techniques into essentially two classes: numerical methods and intuitive methods [10].

Numerical methods or quantitative methods rely on historical data and assume that trends will extend into the future. These numerical methods are then further classified into time-series models and causal models. The time series approach involves the analysis of linear and exponential trends, cyclical changes, and combined linear and cyclical changes. For time series methods, moving averages are most common. Figure 2 below presents the breakdown of various moving averages.

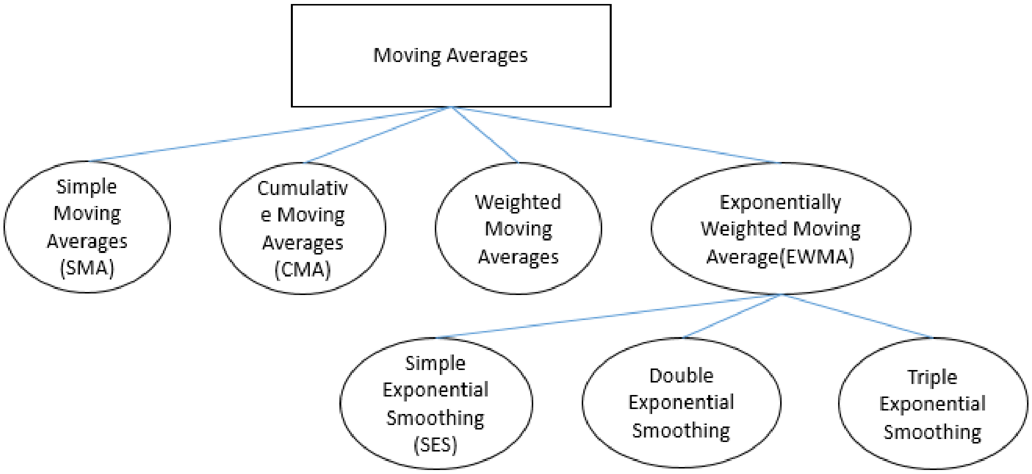


Figure 2. Types of Moving Averages

First, the Simple Moving Average (SMA) and Cumulative Moving Averages (CMA) are the most basic of the moving averages. Exponentially Weighted Moving Average (EWMA) is an alternative way to produce weighted moving average of past data [11]. Simple Exponential Smoothing (SES) is the standard technique for exponentially weighted moving averages. Here, the weights are assigned in geometric progression, with the heaviest weights given to more recent information and older observations are given successively smaller weights. With the combination of the past observations and a smoothing constant α, forecasts for the next time period are computed. These forecasts are most useful when a time series has no trend or seasonal patterns [11]. However, EWMA does have extensions in Double Exponential Smoothing (Holt's) and Triple Exponential Smoothing (Holt Winters) which are used specifically for trends and seasonality respectively. As a weakness, Archer comments that because of compound growth assumption inherent in geometric progressions, exponential smoothing is not ideal for medium or long range forecasting [10].

The second class of numerical methods that Archer mentions is causal methods which involve the analysis of data for other variables considered to be related to the response variable of interest. This technique involves multi-variable regression analysis to forecast future levels of demand. Because of the nature of this technique, when compared to the time-series methods it is much more event-dependent than time dependent [10].

Lastly, the qualitative methods such as the famous Delphi technique mentioned by Archer are used when little historical data exists, or when the trend of the historical data is expected to change. These methods rely on the experience and practical knowledge of experts in the field. In the end, even with long-established approaches, there's a subjective nature to forecasting. Archer ends his paper commenting, "The soundest techniques appear to be those which combine rigorous quantitative analysis with a consensus of expert opinion." [10]

Defining Intermittent Demand

While the practice of forecasting regular demand has been relatively well established and researched, forecasting irregular and sparse demand is still a growing field. Intermittent demand is characterized by random "lumpy" periods of demand and frequent intervals in which there is zero demand. In addition, there are often large variations in size and pattern between each period's requirements. Often these demands also come with no trends or seasonality, adding to forecast difficulty. Consequently, intermittent demand is a significant problem for planners as it occurs in many manufacturing and service industries. Some of the most popular issues arise in spare parts inventory management and stock control problems.

Depending on the forecaster, the concept of intermittent demand is defined differently. Smart defined intermittent demand as a series with at least 30% of zero demand [12]. A US Navy representative considers demand series with less than or equal to 60-70% non-zero demands to be intermittent [13]. Boylan presents a good practical definition for intermittent demand: “As a guideline, at least 20% of the intervals should have zero demand for you to count the demand pattern as intermittent.” [14] However, based on the forecast of interest, there is a wide range of what the historical demand may look like.

Forecasting Metrics for Intermittent Demand

While determining the most suitable forecasting strategy is an important step in predicting future outcomes, evaluation and measuring forecast accuracy is just as essential. Calculating forecast errors overtime can help determine whether certain forecasting techniques match the data and also help determine which methods are most appropriate. The conventional forecast-error metrics include Mean Absolute Deviations(MAD) sometimes also known as Mean Absolute Error, Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). These error metrics all differ slightly and when comparing forecasting results can lead to different conclusions. For example, unlike the MAD, the MSE penalizes the same forecasting technique at a greater cost for large errors than for smaller errors. In addition, the MAPE allows forecasters to compare across time series and different scales [11]. Each serves its own purpose in providing forecast accuracy metrics.

However, when it comes to forecasting intermittent demand, traditional paths have the potential for issues. Hyndman, a relevant contributor in the field of forecasting, highlights some of these issues in his article, "Another Look at Forecasting-Accuracy Metrics for Intermittent Demand." First, Hyndman explains some of the general issues that may result when calculating the usual error metrics. For example, while MAD may be the easiest to understand and compute, it cannot be compared across different time series because it's scale dependent. A similar argument can be made about MSE. While the percentage errors can be free from this scale concern, they become infinite or undefined when there are zero values in a series [15]. As mentioned in this literature review, time periods with zero values is one of the defining characteristics of intermittent demand.

As a result of these shortcomings, Hyndman proposes a scale free error metric for forecasts called the Mean Absolute Scaled Error (MASE). The author emphasizes that the MASE can be used to compare forecasts across series and can handle the periods with zero values. The scaled error described in the article is less than one if it comes from a better forecast than the average one-step naïve forecast computed in the sample. If it is greater than one, than the forecast is worse [15]. Although the other error metrics are important and can provide valuable insight, the MASE is free from the possible roadblocks mentioned making it extremely relevant in intermittent data forecasts.

Forecasting Intermittent Demands

The irregular and lumpy nature of intermittent demands make it very difficult for planners and managers to determine clear procedures for accurate meaningful forecasts. But in some cases, this level of lumpiness may serve as a factor in determining which forecasting method is most appropriate [9]. It has been mentioned in many studies that traditional forecasting methods are inappropriate for intermittent lumpy demands [14] [16] [8] [7]. An early but informative work discussing forecasting of intermittent demand is “A Framework for Forecasting Uncertain Lumpy Demand” by Bartezzaghi et. al. Written in 1994, one of the main objectives of the authors was to, “compare the performances of the forecasting methods and therefore to identify their domain of applicability according to the level and type of demand lumpiness” [9]. Coming from a management and sales perspective, the authors considered three forecasting techniques: the traditional EWMA, Early Sales (EaSa), and Order Overplanning (OrOv). The Early Sales method took actual initial sales numbers and with a Baysian use of information, forecasted out into the future. In contrast, the Order Overplanning method used as a forecasting unit each single customer order instead of the overall demand. This information serves to estimate likely requests from each customer. Figure 3 showed that EWMA performed better when the number of potential customers is high and is inadequate when the number of customers is low. Through experimental simulation, the major takeaway was that EWMA appears only applicable with low levels of lumpiness [9].

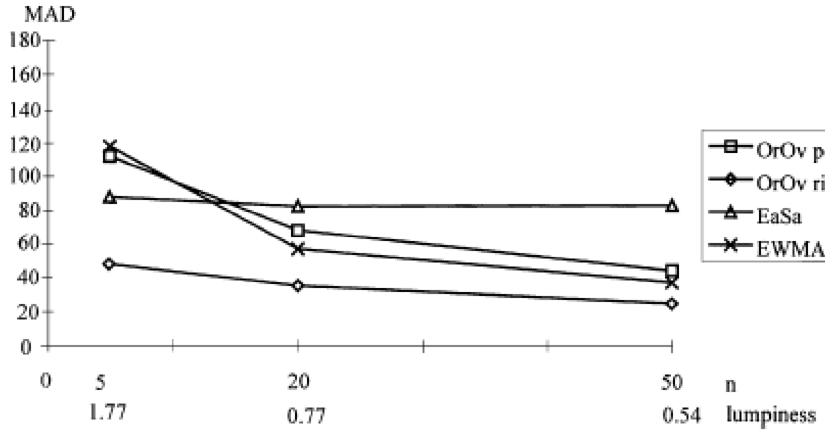
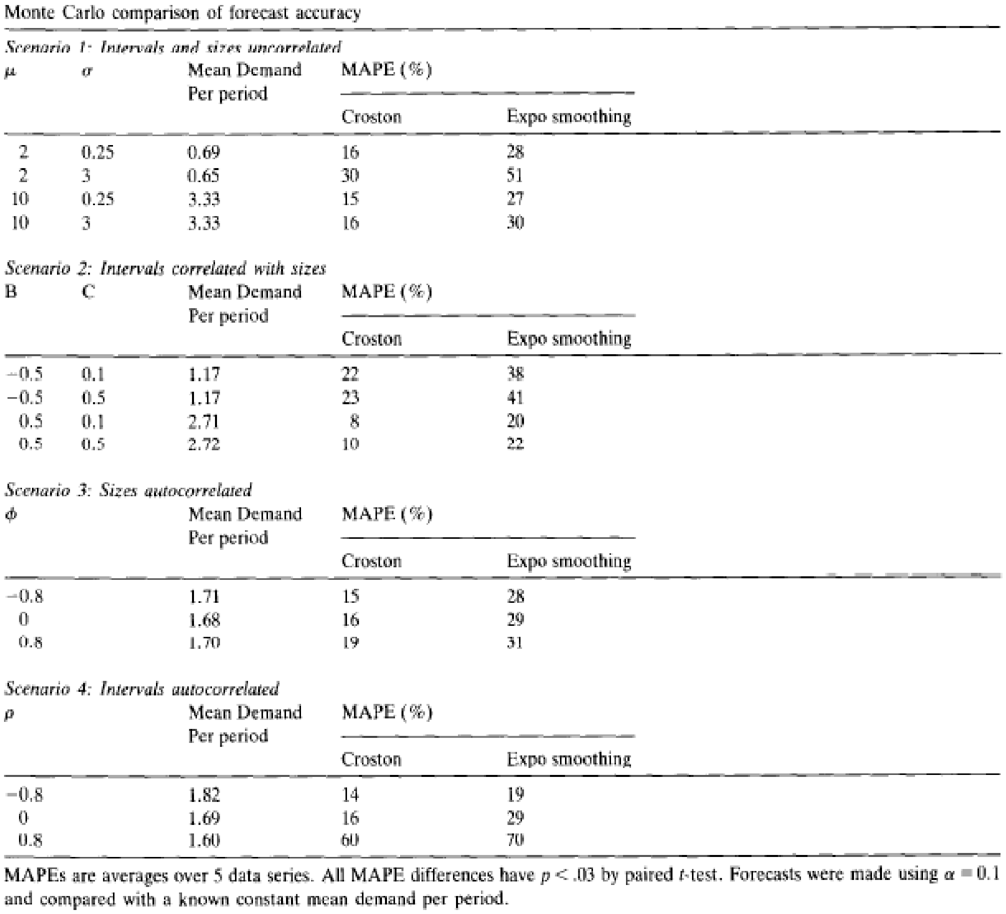


Figure 3. Mean Absolute Error (MAD) for each method [9]

Even with its shortcomings, EWMA still remains one of the classical methods of forecasting intermittent demand. In one of the most heavily cited works on intermittent demand [16], Croston notes some of EWMA's issues and suggests an improved technique for forecasting lumpy demands. Though written in 1972, Croston's corrected method [17], is now applied in major software packages for statistical forecasting and is referenced in almost every research involving intermittent demand. In his paper, Croston [16] argues that when faced with intermittent demand traditional techniques such as EWMA can lead to serious errors. He observed that placing greater weights on the most recent demand period led to estimates that were highest right after a demand occurrence and lowest just before one. As a result, a planner would have a bias and unnecessarily high numbers for stock control. To account for this bias, Croston's method proposed using both the average interval between nonzero demand occurrences and the average size of the occurrence to stabilize the forecast. By doing this, if a review period has no demand, the method just accounts for time periods since the last demand. The estimations are only updated when demand occurs and remains constant otherwise. If demand were to occur at every period, Croston's method would be identical to single exponential smoothing. Croston's method has a number of assumptions. First, the distribution of non-zero demand sizes and the distribution of inter-arrival times are independently and identically distributed. Secondly, the demand sizes and inter-arrival times are mutually independent. With this modification, Croston hoped to address the bias caused by intermittent nonzero demand periods [16].

These recommendations presented by Croston have been influential in forecasting research. Willemain et al [6], another highly involved participant in the field of intermittent demand forecasting, later attempts to directly compare Croston's method and the classic EWMA method on a series of artificial data and actual industrial data. This comparison is executed in two ways: (1) a Monte Carlo comparison using artificial data that purposely violates Croston's assumption of independence and normality and (2) with actual industrial data from four different industries. The results for the Monte Carlo simulation seen in Table 1 show that in all cases, Croston's method showed more accurate estimates of forecast accuracy. The Mean Absolute Percentage Error (MAPE) for Croston's method were generally 10-20 points lower than for EWMA.

Table 1. Monte Carlo comparison of Croston's EWMA [6]



Monte Carlo comparison of forecast accuracy

Scenario 1: Intervals and sizes uncorrelated

μ	σ	Mean Demand Per period	MAPE (%)	
			Croston	Expo smoothing
2	0.25	0.69	16	28
2	3	0.65	30	51
10	0.25	3.33	15	27
10	3	3.33	16	30

Scenario 2: Intervals correlated with sizes

B	C	Mean Demand Per period	MAPE (%)	
			Croston	Expo smoothing
−0.5	0.1	1.17	22	38
−0.5	0.5	1.17	23	41
0.5	0.1	2.71	8	20
0.5	0.5	2.72	10	22

Scenario 3: Sizes autocorrelated

ϕ	Mean Demand Per period	MAPE (%)	
		Croston	Expo smoothing
−0.8	1.71	15	28
0	1.68	16	29
0.8	1.70	19	31

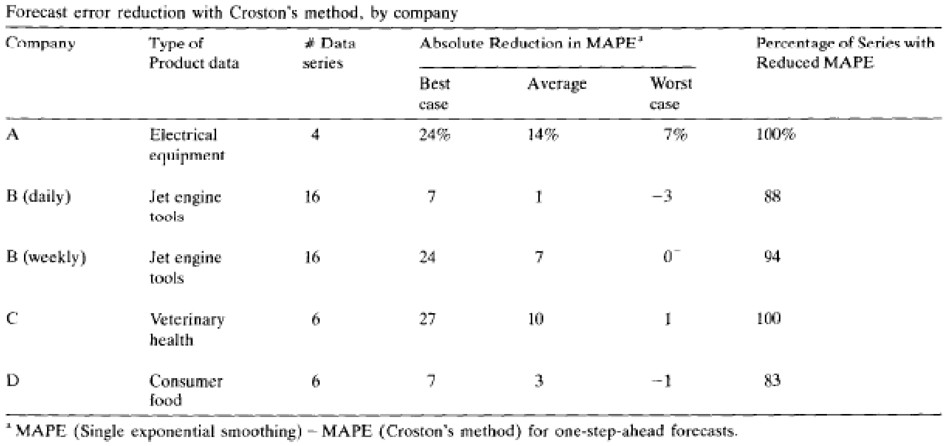
Scenario 4: Intervals autocorrelated

ρ	Mean Demand Per period	MAPE (%)	
		Croston	Expo smoothing
−0.8	1.82	14	19
0	1.69	16	29
0.8	1.60	60	70

MAPEs are averages over 5 data series. All MAPE differences have $p < .03$ by paired t-test. Forecasts were made using $\alpha = 0.1$ and compared with a known constant mean demand per period.

For the comparison using industrial data, Croston's method was again shown to be superior. The results can be seen in Table 2 where on average Croston's method was more accurate for all four companies' data. In all scenarios Croston's method is robustly superior to exponential smoothing but in some cases, only showed modest benefits.

Table 2. Comparison of Croston's and EWMA for Industrial Data [6]



Forecast error reduction with Croston's method, by company

Company	Type of Product data	# Data series	Absolute Reduction in MAPE[a]			Percentage of Series with Reduced MAPE
			Best case	Average	Worst case	
A	Electrical equipment	4	24%	14%	7%	100%
B (daily)	Jet engine tools	16	7	1	−3	88
B (weekly)	Jet engine tools	16	24	7	0^-	94
C	Veterinary health	6	27	10	1	100
D	Consumer food	6	7	3	−1	83

[a] MAPE (Single exponential smoothing) − MAPE (Croston's method) for one-step-ahead forecasts.

An interesting comment in Willemain et al. [6] is that Croston's method shows the smallest improvement for daily data forecasting in Company B which had the largest portion of zero values. The authors suggest that, "there may be some optimal degree of intermittency, from the point of view of switching from exponential smoothing to Croston's method. Perhaps too many zero values make it essentially impossible to forecast well using any statistical method, while too few zero values make it unnecessary to abandon exponential smoothing" [6].

Only a couple years after the article by Willemain et al, Johnston and Boylan revisit these questions in their paper from 1996 by digging deeper into the comparison of Croston's method and EWMA [18]. While Croston suggested estimating the average interval between demand and the average size he did not go on to estimate the variability of demand. In this paper, the authors compares Croston's method to conventional EWMA estimators to find further insight into determining the appropriate method. Their main finding was that the average inter-demand interval must be greater than 1.25 review periods to realize the advantages of Croston's method over EWMA [18].

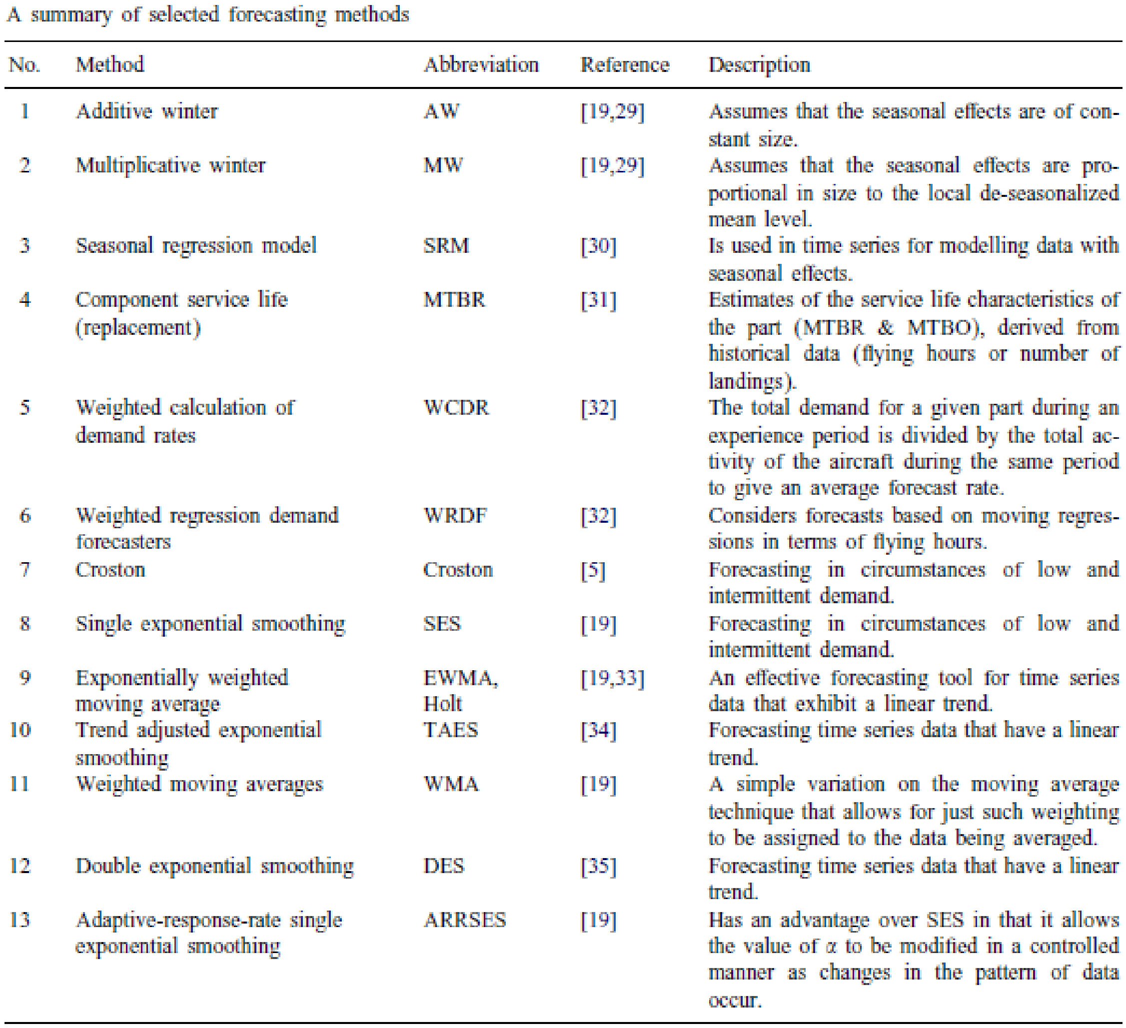
As more research became available through time, criticism using Croston's method have emerged and improvements have been proposed. More recently, Syntetos and Boylan [7] have claimed that a positive bias in Croston's mathematical derivation of the expected estimate of demand contributes towards only modest improvements when compared to traditional methods like EWMA. Syntetos and Boylan comment, "Croston's separate estimates of the demand size are correct, but if combined as a ratio fail to produce accurate estimates of demand per time period" [7]. The authors introduce a revision to Croston's method that approximates an unbiased demand per period estimate for the method.

Later, Syntetos and Boylan [19] deliver further modification to the mean estimator in Croston's method. This modification is known as the Synteto-Boylan approximation (SBA). The key change made was accounting for bias due to division. With this new method, the authors applied four forecasting methods – SMA(13 periods), SES, Croston's method, and SBA- on intermittent data from the automotive industry. Comparisons were made considering various criterion including mean errors, scaled mean errors, and geometric root-mean-square errors. They concluded that Croston's method performed better only for low values of the smoothing constant and the bias becomes pronounced for values above 0.15. Overall, SBA was recognized as the more accurate estimator for the data investigated [19].

While the SBA method has been proven to correct the positive bias in Croston's method, there is also another important disadvantage worth exploring. Because Croston's method and SBA are designed to only update after occurrences of nonzero demand, it could run into issues with obsolescence. Forecasts run the risk of becoming outdated after many periods of zero demand or dead stock. To account for this concern, Teunter et al. [20] propose a unique forecasting method than can deal with intermittent demand and obsolescence. Instead of updating the demand intervals, their method updates the probability of demand. The main advantage of their method is that while the demand intervals can only be updated after positive demand, demand probability can be updated at any time period. More importantly, the method is able to quickly adapt to situations where sudden obsolescence occurs and make adjustments accordingly. The results presented in the researchers' paper show reasonable benefit in the new technique. However, the authors emphasize that figuring out the best values for smoothing constants can be a complicated task that sways the performance of forecasts [20].

A final piece relevant to forecasting intermittent demands is Ghobbar and Friend's [8]. Focusing on spare parts in the aviation industry, the main objective of this study was to analyze a mix of thirteen different forecasting methods and develop a predictive model for each [8]. These thirteen forecasting methods included both traditional and some specialized methods used by aviation companies (Table 3).

Table 3. Forecasting Methods Analyzed [8]



A summary of selected forecasting methods

No.	Method	Abbreviation	Reference	Description
1	Additive winter	AW	[19,29]	Assumes that the seasonal effects are of constant size.
2	Multiplicative winter	MW	[19,29]	Assumes that the seasonal effects are proportional in size to the local de-seasonalized mean level.
3	Seasonal regression model	SRM	[30]	Is used in time series for modelling data with seasonal effects.
4	Component service life (replacement)	MTBR	[31]	Estimates of the service life characteristics of the part (MTBR & MTBO), derived from historical data (flying hours or number of landings).
5	Weighted calculation of demand rates	WCDR	[32]	The total demand for a given part during an experience period is divided by the total activity of the aircraft during the same period to give an average forecast rate.
6	Weighted regression demand forecasters	WRDF	[32]	Considers forecasts based on moving regressions in terms of flying hours.
7	Croston	Croston	[5]	Forecasting in circumstances of low and intermittent demand.
8	Single exponential smoothing	SES	[19]	Forecasting in circumstances of low and intermittent demand.
9	Exponentially weighted moving average	EWMA, Holt	[19,33]	An effective forecasting tool for time series data that exhibit a linear trend.
10	Trend adjusted exponential smoothing	TAES	[34]	Forecasting time series data that have a linear trend.
11	Weighted moving averages	WMA	[19]	A simple variation on the moving average technique that allows for just such weighting to be assigned to the data being averaged.
12	Double exponential smoothing	DES	[35]	Forecasting time series data that have a linear trend.
13	Adaptive-response-rate single exponential smoothing	ARRSES	[19]	Has an advantage over SES in that it allows the value of α to be modified in a controlled manner as changes in the pattern of data occur.

Again, the analysis in this study was for aircraft parts which had previously received little attention. Though low in demand, the spare parts studied are critical to operations and their unavailability can lead to excessive downtime costs. The results in this study support superiority of moving averages and Croston's method for intermittent demand whereas other methods were found to be questionable. Like most of the other studies and research advised, traditional forecasting techniques in this analysis were shown to be inappropriate for parts with sporadic demand [8]. One interesting discovery mentioned by the authors is that, “the weighted moving averages were much superior to exponential smoothing and could provide tangible benefits to airline operators and maintenance service organizations forecasting intermittent demand” [8]. The authors even go on to recommend that companies should reconsider even using inappropriate techniques such as SES for their forecasts. While a thorough comparison of every single one of these techniques has not been conducted, these models presented give paths for further research.

Categorizing Intermittent and Lumpy Demands

There is often confusion when it comes to a standardized definition of intermittent demand and words such as lumpy demand, sporadic demand, erratic demand, and sparse demand are frequently used interchangeably. To better understand and analyze these diverse demands, there have been attempts to categorize demand scenarios. One of the earliest attempts at a demand categorization scheme was by Williams [21] in an inventory system study from 1984. Figure 4 shows this approach. His categorization method is first based on intermittence or how often the demand occurred during the lead time. Secondly, the lumpiness or variance of non-zero demand was also considered. Category B in his categorization scheme represents slow-moving inventory while Categories D1 and D2 represents highly sporadic demand with high intermittence and high lumpiness. All other categories have been classified as smooth. A major issue with this categorization scheme is that the cut-off values are based on the specific inventory system that Willams studied, making it unsuitable for general demands.

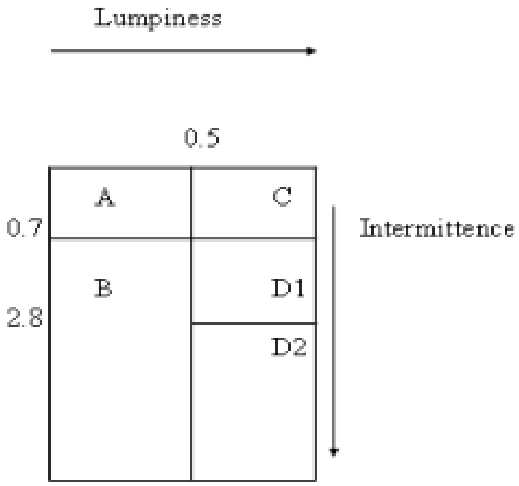


Figure 4. Williams' Categorization Scheme [21]

Another pursuit for the systematic and practical categorization of intermittent demands was by Syntetos et al. [22]. They conducted their study by comparing the Mean Square Error (MSE) of three forecasting techniques: SES, Croston’s Method, and the Syntetos' Boylan Approximation (SBA). Based on these results, the authors proposed a scheme with recommendations for appropriate cut-offs for squared coefficients of variation and mean interval between non-zero demands. Figure 5 presents their proposal where Region 1 indicated erratic demand, Region 2 indicated lumpy demand, Region 3 indicates smooth demand, and finally Region 4 indicates intermittent demand. This scheme also considers demands with a high percentage of zero demands. Furthermore, using this categorization scheme, strategies in selecting the optimal forecasting method are explored.

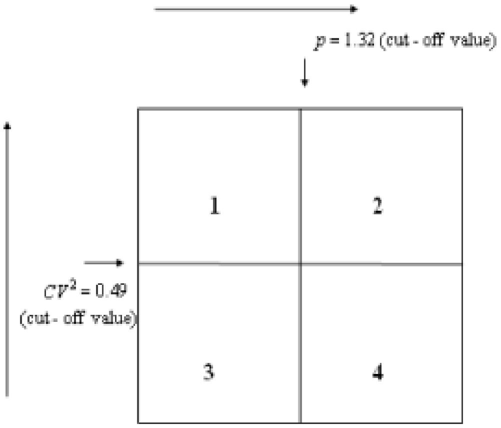


Figure 5. Syntetos' Categorization Scheme [22]

This concept of categorizing intermittent demand series and identifying the best forecasting technique is further examined by Varghese and Rossetti [23]. Instead of creating a scheme exclusively based on MSE such as the Syntetos et al. [22] study, Varghese and Rossetti incorporated Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE). Depending on the technique, the winner for the best forecasting technique may be different across each of the error metrics. Consequently, Varghese and Rossetti used an equal weighted error based on the scaled errors of MAD, MSE, and MAPE. Also, the study used the same forecasting methods used in the Syntetos study but cumulative average as a fourth method. Their analysis suggested significant benefits in using their chart-recommended forecasting technique in order to improve overall forecasting accuracy.

All of these classification methods have been established on forecast error. As a final recommendation Varghese and Rossetti insist better classification approaches should be based on the best forecasting technique itself rather than forecast error [23].

Some future paths include using Multinomial Logistic Regression, Discriminant Analysis, Artificial Neural Networks, and other unconventional techniques.

Department of Defense's Commercial Railcar Assets

Railroads are one of the most critical assets in military transportation. For over a century, the U.S military has used the expansive railroad network to move heavy tanks, trucks, and even rocket engines between military bases [4]. For services with heavy vehicles and equipment such as the U.S Army, DoD and commercial railcar assets are heavily relied on to transport its wheeled/tracked vehicles to destinations in order to meet prescribed mobilization or deployment timelines. In a 2013 report, the DoD has access to 5,862 flat rail cars. Of those, 4,504 are owned by commercial railroads and the DoD owns the remaining 1,358 [4]. These heavy lift railcars transport Army heavy tanks such as the M1 Abrams and are capable of moving up to two tanks each. This kind of capability is vital to meeting requirements for military training exercises, special missions, and deployments.

As the head organization, U.S Transportation Command (USTRANSCOM) oversees the movement of all military equipment in and out of war zones. Within USTRANSCOM, there are two major methods to military rail operations. Traditionally, the DoD has conducted most of its military mobilizations and deployments through the commercial industry. As a result, the US military is heavily dependent on the commercial rail carriers to transport equipment and supplies from point to point in support of real world exercises and contingencies [24]. With more than 140,810 miles of track, the US has one of the most extensive rail networks (see Figure 6) owned by different rail carriers [25]. The DoD utilizes a mix of these commercial carriers to meet their logistic requirements. Having this commercial partnership and capability is an invaluable boost to military logistics and transportation.

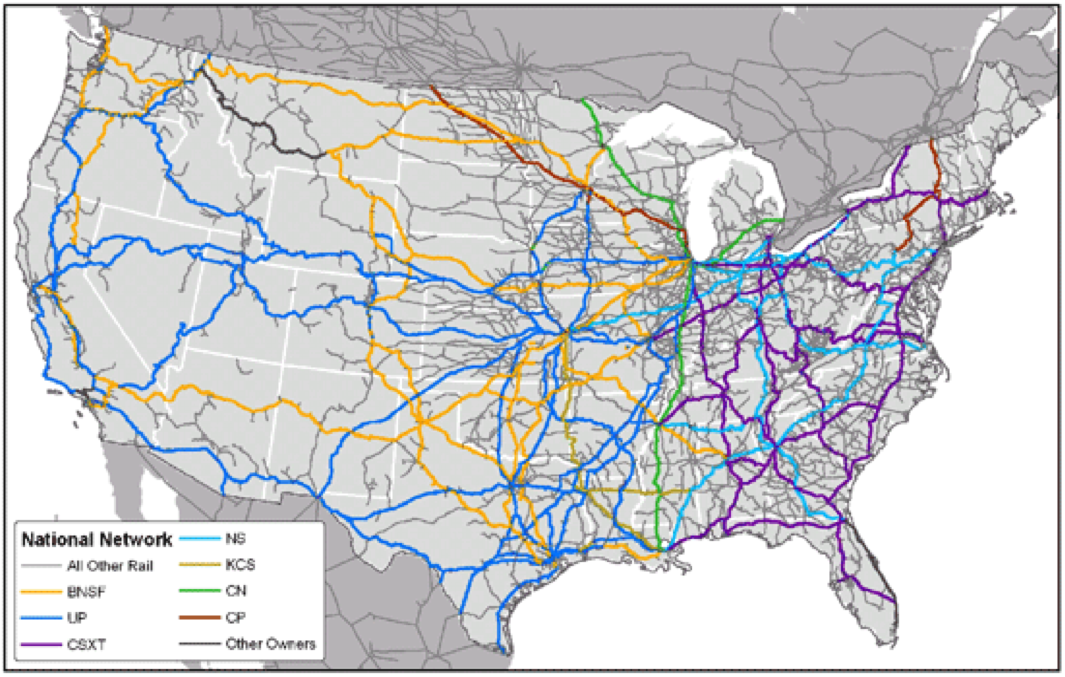


Figure 6. US Freight Rail Network [25]

Secondly, dedicated DoD owned railcars make up the other side of military transportation. These assets play a critical role especially when commercial support is not available. Sones' [24] thesis studying the DoD's railcar inventory points out the three elements that make up the DoD's railcar fleet. For this study, the main fleet of interest is the Defensive Freight Rail Inventory Fleet (DFRIF), which consists primarily of heavy lift rail flatcars. DFRIF is made up of railcar assets required by DoD to conduct both normal peacetime and surge deployment operations.

In an article in the Army Logistician, the author breaks down the roles DFRIF plays in military planning [26]. DFRIF fills the gap created when railroads don't have sufficient traffic to meet DoD needs. In addition, because the DFRIF is owned by the DoD, the railcars are free to be placed strategically at installations directly according to mobilization needs [26]. As dedicated assets to an intricate railway logistics system, proper planning for the utilization of these railcars makes forecasts invaluable to planning organizations.

Rail Freight Fleet Management

Rail freight cars are extremely expensive and appropriate vehicle fleet management is an important problem for all rail freight logistics planners. Because of the size and complexity of these problems, a vast literature has been devoted to finding insight on the many aspects of rail freight transportation and distribution. One of the greatest areas of concern is the cost efficient utilization of railcars. Dejax and Crainic's [27] found that a significant amount of all rail movements traveled are carried out by empty vehicles. It was estimated that in the US rail system, for 40% of the time of the average car cycle, the car is empty [27]. These inefficiencies not only lead to needless transportation costs, but also result in unnecessary wear and tear to the vehicles. Dejax and Crainic's 1987 survey looks into some of the early deterministic and stochastic models to fleet sizing. When it comes to fleet sizing, determining the given demand for loaded trips (number of trips leaving each node of the network) and the characteristics of each trip (length, time, etc) is critical. Furthermore, the authors state that when it comes to fleet managements, “the lack of an appropriate and reliable information system on empty vehicle freight availability and demand is often mentioned as a major problem by researchers as well by practitioners.” [27] At the time, only two models designed specifically for freight vehicle transportation were available [28] [29]. These early models are conceptually straightforward and were proved somewhat helpful but, improved statistical research has been recommended.

Later research examined optimal fleet management to minimize overall rail freight transportation costs and inefficiencies for organizations. Sherali and Maguire [30] observed that in the past, shippers relied on proprietary planning schemes that used peak month demand to size their fleets. The authors comment that the shipper’s primary concern was insuring a 100-percent car availability at all times, which resulted in poor railcar utilization. In other words, the railroads employed an overly conservative approach that resulted in high capital costs and affected the rates charged to the shippers. The researcher’s improved approach presented a combination of static and dynamic mathematical models. The static models were relied on to conduct hypothetical fleet sizing exercises to gain better insight into the flows between origins and destinations. This data would provide useful cost information where one would seek to minimize the total empty railcars. Despite their value, a major weakness to the static models is that they simply use average values and ignore the possible variations in day to day activities. To account for this shortcoming, the dynamic models presented offer a more sophisticated representation of loaded and empty railcar flows through simulation. The practice of this method’s suggestions have evolved through time but have been shown to provide cost benefits for the users mentioned in the paper. As more data and results become available, these types of methods continue to evolve.

More recently, newer models relying on optimal control theory have been developed. Bojovic [31] created a model which attempted to address the enormously expensive rail freight cars and managing the railroad's capital resources. His research aimed to determine the optional number of railcars that would satisfy demand, on one hand, and would minimize the total cost on the other. In the end, his results showed to be helpful for making fleet investment decisions. However, one weakness to the model is that a large number of important aspects are assumed for actual model application.

Summary

This literature review presented background information on rail transportation's role in the DoD's military logistics and also examined its commercial and organic assets. Not only does accurate forecasting provide these logistical planners insight, but accurate forecasts can be the key to drive other powerful tools. The review then briefly covered the traditional forecasting techniques in the field for general demand emphasizing time series techniques like moving averages and exponential smoothing. Next, a working definition and explanation of intermittent/lumpy demand was introduced. Finally, a detailed review of past literature on forecasting intermittent demand was explored including accuracy metrics for forecasts.

III. Methodology

Chapter Overview

USTRANSCOM operates and maintains numerous Contiguous United States (CONUS) locations for rail transportation and logistics. Producing and analyzing forecasts for each of these locations is invaluable for forecasters as many times these train demands tend to be sparse and intermittent. This section presents the procedures used to produce and optimize the railcar demand forecasts. The research effort is divided into five main steps. First, the data is collected and compiled into individual time series based on railcar types and shipping origins. Next, initial data exploration is conducted to scope and categorize the time series data based on patterns and intermittency. The third and fourth steps then establish potential forecasting techniques and the accuracy metrics that drive these methods. Finally, these forecasting methods are optimized using statistical software and forecasting results are produced for data analysis.

Scope and Data Description

Before creating forecasts, the data must be organized and aggregated into a useable format. Fortunately, USTRANSCOM's Surface Deployment and Distribution Command (SDDC) records all rail freight movement by the DoD. These records track vital information such as the date, origin, destination, railcar type, and mission descriptions for all rail activity. Each month's train demands are aggregated into a collection of time series. This dataset is filtered and organized to historical monthly time series demands of all railcars by origins for four years. (Jan 2011 to Dec 2014). In total, there are 123 different origins each with 48 monthly railcar demands time periods. In order to further capture specific railcar demands from each location, these 123 locations were then further broken down by railcars types. A list of different railcar types and their equipment codes have been provided in Appendix A. After the railcars are divided by the location's railcar type, the result is 241 time series demands of specific railcars for 48 time periods. This filtered dataset is found in Appendix D.

Organizing the dataset in this manner paves the path for applying time series forecasting methods on the specific railcar demands for each location. Not only has the data been transformed into demands by time, it is now organized in a way where the demand for a certain commodity can be tracked down to the origin. Forecasts for these time series provide planners with a more detailed picture on which types of railcars need to be where at precise times.

Data Exploration

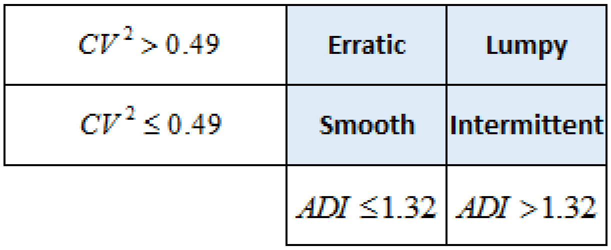
Before any forecasts are conducted, it is worthwhile to do some initial data exploration to capture any characteristics of interest in the data. As suggested in the literature by Syntetos and Boylan **[22]**, a demand categorization scheme is applied on the demand series' based on the average inter demand intervals (ADI) and the squared coefficient of variation (CV^2). Here, the ADI is the average number of time periods between two nonzero demands which indicates the level of intermittence,

$$ADI = \frac{\sum_{i=1}^{N-1} t_i}{N-1} \qquad \textbf{(1)}$$

where N represents the number of periods with non-zero demand and t_i is the interval between two consecutive demands. Furthermore, CV^2 is simply,

$$CV^2 = \left(\frac{\sigma}{\mu}\right)^2 \qquad \textbf{(2)}$$

which is the ratio of the standard deviation and mean squared. With these derived parameters, the demands are categorized using cutoffs suggested by Syntetos and Boylan (See Figure 7) [22].

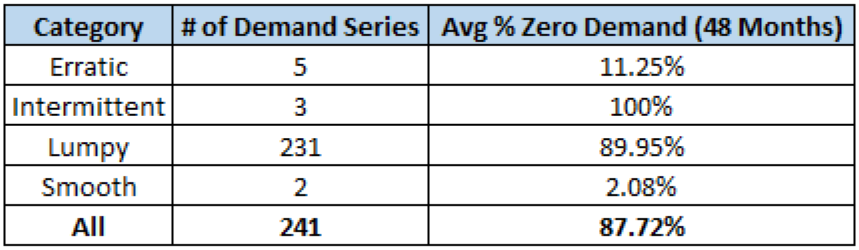


$CV^2 > 0.49$	Erratic	Lumpy
$CV^2 \leq 0.49$	Smooth	Intermittent
	$ADI \leq 1.32$	$ADI > 1.32$

Figure 7. Syntetos and Boylan Data Categorization Scheme [22]

Based on this categorization scheme, 231 of the 241 or 95.85% of train demand time series were categorized as 'lumpy." Furthermore, the other time series were categorized as erratic: 5/241, smooth: 2/241, and intermittent: 3/241. However, all three cases of the "intermittent," time series did not have a single occurrence of nonzero demand over the four years as seen in Table 4. For those time series that were categorized as lumpy, the average percent of zero demand in 48 time periods was 89.95% and 87.72% overall. These numbers imply that the dataset is primarily composed of the irregular lumpy demands referenced in this paper. In addition, the average percent of time periods with zero demand suggests that the dataset is extremely sparse.

Table 4. Categorization Results and Intermittency



Category	# of Demand Series	Avg % Zero Demand (48 Months)
Erratic	5	11.25%
Intermittent	3	100%
Lumpy	231	89.95%
Smooth	2	2.08%
All	**241**	**87.72%**

By examining and categorizing the dataset, there is potential for analysis on finding systematic methods on selecting forecasting methods. In addition, it allows the researcher to better understand the demand's behavior.

Selection of Forecasting Techniques

This section presents the time-series forecasting methods applied in this research. Five main methods are utilized in this study. These methods were selected since they were found to be utilized specifically for forecasting intermittent demands in the literature. While many of the methods are traditional approaches in most academic and commercial fields, some are more recent and are yet to be further explored. Each method is briefly explained.

Simple Moving Averages (SMA)

Moving averages are some of the most popular techniques for forecasting demand levels. These moving averages are typically used in time series data to smooth out fluctuations and adapt to trends and cycles. The most basic type of moving average is the simple moving average. A simple moving average is the mean of the previous *k* observations. The general equation for SMA is as follows:

$$\hat{Y}_{t+1} = \frac{Y_t + Y_{t-1} + ... + Y_{t-k+1}}{k} \qquad \textbf{(3)}$$

where :
$\hat{Y}_t$ = forecast value at time period *t*
Y_t = actual value at time period *t*.

The main advantage of these forecasts is that they find a middle ground in adapting to the cyclical patterns and are not too sensitive in random shocks in the data from one time period to the next. However, because the mean is not centered, the simple moving average tends to lag behind the most recent observation. When *k*=1, the simple moving average becomes a naïve forecast where each future forecast is equal to the historical value from the previous time period. Or more simply, $\hat{Y}_{t+k} = Y_t$.

Simple Exponential Smoothing (SES)

Another form of moving averages is exponentially weighted moving averages. The most basic of this class is simple exponential smoothing. This method is used when there is no trend or seasonal pattern in the data. While SMA treats the last *k* observations equally and ignores all preceding observations, SES incorporates all data in the time series. However, it gives more weight to more recent values assuming they are more relevant to predicting future forecasts. This method takes the form:

$$\hat{Y}_{t+1} = \alpha Y_t + (1-\alpha)\hat{Y}_{t-1} \qquad \textbf{(4)}$$

where :
$\hat{Y}_{t+1}$= forecast value for period t+1
$\hat{Y}_{t-1}$= forecast value for period t-1
Y_t = actual value at time period t
α = smoothing parameter

The smoothing parameter plays an important role to the method as it determines how much weight goes to the most recent observation. High α values give more weight to recent observations while low α values emphasize historical values. Here when α =1, SES becomes equivalent to a naïve forecast. The exponential attribute is seen as the weights affect the future forecasts in a geometric fashion.

Croston's Method

Croston's method [16] is a technique that has been specialized for dealing with intermittent and slow moving demand. The method is essentially a modification of SES where non-zero demand sizes and periods between non-zero demands are smoothed separately creating an estimate of demand per period. Demand rate forecasts are updated only after demand occurrences. Before the procedures for Croston's method are presented, consider the following notation. Let:

Y(t) = the estimate of the mean size of a nonzero demand at time t
P(t) = the estimate of the mean interval between nonzero demands at time t
X(t) = the actual demand at time t
Q = the time interval since the last nonzero demand
α = smoothing parameter between 0 and 1
F(t) = demand rate forecast at time t

Figure 8 illustrates the steps to Croston's Method by Sahin [32].

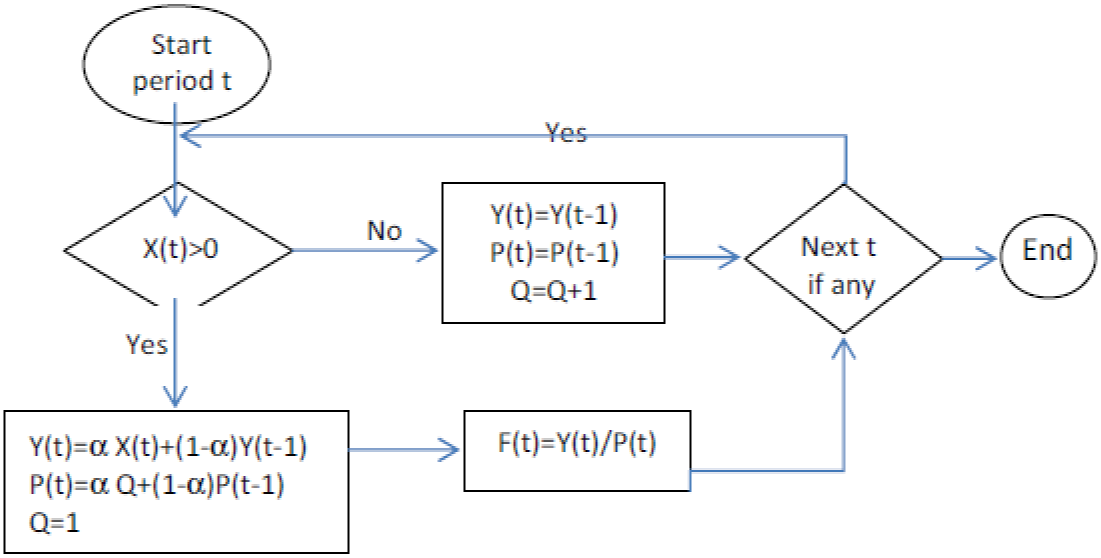


Figure 8. Croston's Method Procedures by Sahin [32]

Again, forecasts are only updated after demand occurrences and remain constant otherwise. If demands were to occur every period, Croston’s method becomes identical to SES. Additionally, Croston’s Method makes three vital assumptions to the process (1) the distribution of non-zero demand sizes is independently and identically distributed (i.i.d) normal, (2) the distribution of the inter-arrival times Q is i.i.d geometric, and (3) demand sizes and inter-arrival times are mutually independent.

Syntetos Boylan Approximation (SBA)

Throughout the years, Croston’s method has been highly researched for its application to sparse slow-moving demands. Syntetos and Boylan [7] found that the original method is biased and proposed a modified version that corrected the problem for improved accuracy. It was found the Croston’s method leads to a positive biased estimate of average demand per unit time. The bias arises because if it is assumed that estimators of demand size and demand intervals are independent, then

$$E(F(t)) = E\left(\frac{Y(t)}{P(\mathrm{t})}\right) = E(Y(t))E\left(\frac{1}{P(t)}\right) \tag{5}$$

However,

$$E\left(\frac{1}{P(t)}\right) \neq \frac{1}{E(P(t))} \tag{6}$$

and therefore Croston's method is biased [1]. The procedures to the corrected Syntetos Boylan Approximation (SBA) are identical to Croston's method but re-estimates the mean demand as follows:

$$F(t) = \left(1 - \frac{\alpha_P}{2}\right)\frac{Y(t)}{P(t)} \tag{7}$$

Here α_P is the smoothing parameter for updated the interdemand intervals.

Teunter Syntetos Babai (TSB) method

Croston's method and SBA forecasts are only updated after periods of non-zero demand causing forecasts to become outdated after long periods of zero demand. The Teunter-Syntetos-Babai (TSB) method accounts for possible obsolescence and dead stock issues by updating the probability of demand instead of demand intervals [20]. In this way, forecasts can be updated after every time period and can make adjustments accordingly. The following notation is introduced:

Y_t = demand for an item at period t
$\hat{Y}_t$ = estimate of mean demand per period at the end of period t for period t+1
z_t = actual demand size in period t
$\hat{z}_t$ = estimate of mean demand size at the end of period t
p_t = demand occurrence indicator for period t, so that:

$\hat{p}_t$ = 1 if demand occurs at time t (i.e Y_t > 0) and 0 otherwise

α, β = smoothing parameters where $0 \le \alpha, \beta \le 1$

Now the forecast updating procedure:

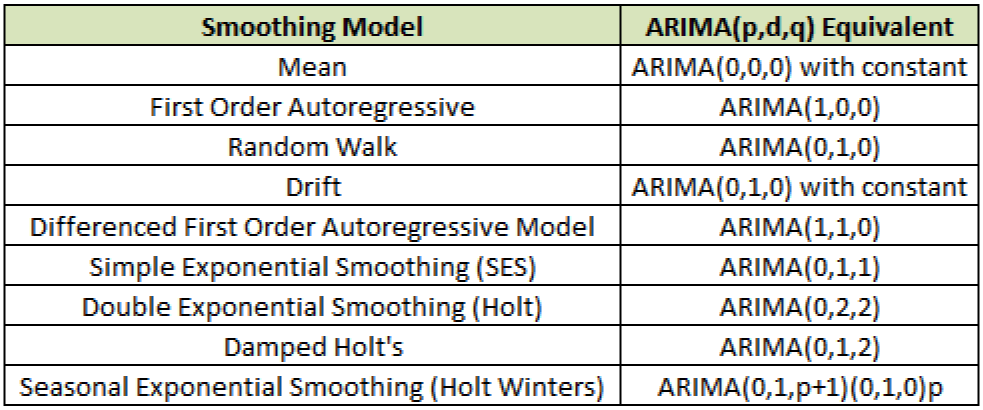
```
If $p_t = 0$ then
    $\hat{p}_t = \hat{p}_{t-1} + \beta(0 - \hat{p}_{t-1})$
    $\hat{z}_t = \hat{z}_{t-1}$
    $\hat{Y}_t = \hat{p}_t \hat{z}_t$
Else ( $p_t = 1$ )
    $\hat{p}_t = \hat{p}_{t-1} + \beta(1 - \hat{p}_{t-1})$
    $\hat{z}_t = \hat{z}_{t-1} + \alpha(z_t - \hat{z}_{t-1})$
    $\hat{Y}_t = \hat{p}_t \hat{z}_t$
End If
```

Similar to some of the other methods, when $\alpha = \beta = 1$ the method becomes equivalent to the naïve method. As mentioned by Teunter et al. [20] determining the right smoothing parameters is critical to the TSB method's performance. Too large values lead to poor performance for stationary demand and too small values make the method too slow in responding to changes in the demand.

ARIMA(Box-Jenkins) Method

The final forecasting method used in this study is the Auto-Regressive Integrated Moving Average (ARIMA) method. Detailed by Box and Jenkins [33], this method generalizes many of the traditional forecasting smoothing equations. Based on the parameters of each ARIMA model, there exists a corresponding special case of a forecasting model. Table 5 presents just some of the common smoothing models linked to ARIMA.

Table 5. Smoothing Models and ARIMA Equivalence



Smoothing Model	ARIMA(p,d,q) Equivalent
Mean	ARIMA(0,0,0) with constant
First Order Autoregressive	ARIMA(1,0,0)
Random Walk	ARIMA(0,1,0)
Drift	ARIMA(0,1,0) with constant
Differenced First Order Autoregressive Model	ARIMA(1,1,0)
Simple Exponential Smoothing (SES)	ARIMA(0,1,1)
Double Exponential Smoothing (Holt)	ARIMA(0,2,2)
Damped Holt's	ARIMA(0,1,2)
Seasonal Exponential Smoothing (Holt Winters)	ARIMA(0,1,p+1)(0,1,0)p

As the name suggests, ARIMA incorporates an auto regressive factor from past values, series differencing, and a moving average term fitted to previous values of noise in the series. Using the convention, ARIMA(*p*,*d*,*q*) where *p* represents the order of the AR term, *d* is the order of the differencing term to ensure the series is stationary with respect to its mean, and *q* indicating the order of the MA term. Currently, USTRANSCOM uses an ARIMA optimizer to run various combinations and output a future forecast. In this study, this ARIMA optimizer will be treated as the baseline method.

Accuracy Metrics

Calculating and comparing the errors between forecasting methods allows thorough analysis of forecasting accuracy. However, depending on the accuracy metric selected, determining the “best” forecast can be a disputable task. This section discusses all of the accuracy metrics and cost functions used in this research.

Mean Average Deviation (MAD)

When it comes to forecasting metrics, mean average deviation (MAD) is the simplest and easiest to understand. MAD measures the absolute deviations for all forecasts. Equivalently,

$$MAD = \frac{\sum_{t=1}^{n} \left| y_t - \hat{y}_t \right|}{n} \tag{8}$$

where:
y_t = the actual value at time t
$\hat{y}_t$ = the forecasted value for time t
n = the total number of observed time periods

Mean Squared Error (MSE)

Another common accuracy metric for forecasts is the mean square error (MSE). These calculations prevent positive and negative forecast errors from cancelling each other out. This measure is simply the average of the squared errors for all forecast.

$$MSE = \frac{\sum_{t=1}^{n} \left(y_t - \hat{y}_t \right)^2}{n} \tag{9}$$

where:
y_t = the actual value at time t
$\hat{y}_t$ = the forecasted value for time t
n = the total number of observed time periods

The major difference between MAD and MSE is that MSE penalizes forecasts much more for large errors than for small ones. When using the MSE, the forecaster would prefer several smaller forecasting errors than a single large error.

Mean Absolute Scaled Error (MASE)

Proposed by Hyndman and Koehler in 2006, mean absolute scaled error (MASE) is an alternative measure to forecast accuracy. Hyndman and Koehler argued that many of the other accuracy metrics are unsuitable for intermittent demand data because they can give infinite or undefined values [15]. The scaled error is defined as,

$$q_t = \frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n}\left|Y_i - Y_{i-1}\right|} \quad \textbf{(10)}$$

$$\text{and MASE} = mean\left(\left|q_t\right|\right) \quad \textbf{(11)}$$

where:
e_t = forecast error at time period t
Y_i = the actual value at time period i
n = the total number of observed time periods
q_t = the scaled error

A scaled error of less than one implies a better forecast than the average one-step, naïve forecast computed-in sample and worse if it is greater than one [15]. MASE equal to one means that the forecast error is equivalent to that of a naïve forecast.

Akaike's Information Criterion (AIC) and AIC Corrected (AICc)

The Akaike's Information Criterion (AIC) is a measure used to compare the relative quality between statistical models. It is one of the more well-known criterions for model selection. First, AIC is defined as,

$$AIC = -2\log(L) + 2k \quad \textbf{(12)}$$

where:
L = the maximum value of the likelihood function for the model
k = the number of estimated parameters in the model

When it comes to comparing AIC's, smaller values are preferred as models are penalized with an increasing number of estimated parameters. The formula for corrected AIC (AICc) is as follows,

$$AICc = AIC + \frac{2k(k+1)}{n-k-1} \tag{13}$$

where:
k = the number of estimated parameters in the model
n = the sample size

AICc puts an even greater penalty for extra parameters preventing the probability of overfitting. Again, AIC and AICc is primarily used to compare different models with each other and does not provide any indication of actual performance. For example, a low AIC and AICc does not mean a model fits well or poorly.

Mean Absolute Rate (MAR)

The final accuracy metric utilized in this study is the mean absolute rate (MAR). Prosposed by Kourentzes [34], this metric was developed with techniques such as Croston's method and SBA in mind. Croston's method and its variant SBA forecast more demand rate over time than an actual expected demand value. First, the cumulative mean at each point forecast is calculated as below,

$$r_i = \hat{y}_i - i^{-1}\sum_{j=1}^{i} y_j \tag{14}$$

where:
y_i = the actual value at time *i*
$\hat{y}_i$= the forecasted value for time *i*
i = the time period *i*
From r_i , the MAR can be calculated as follows,

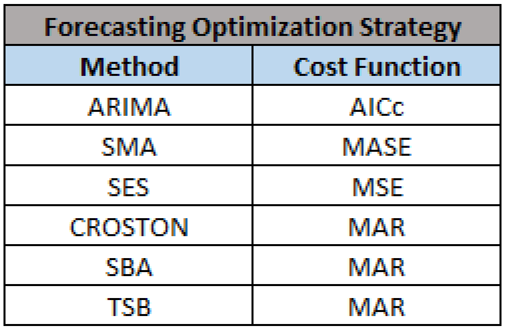
$$MAR_n = \sum_{i=1}^{n} |r_i| \tag{15}$$

Kourentzes claims that accuracy metrics like MAR are more meaningful to these techniques and more importantly have the potential to perform better when considered as a cost function [34].

Optimization for Intermittent Demand Forecasts

The established forecasting methods are then optimized based on select cost functions to find the best forecast for each time series in the dataset. As mentioned previously, rail movement demand data has been filtered down into a collection of time series for four years. This four year worth of data is split into a two sets. The first three years are used as the initialization or training set and the last year of data is used for validation or the "testing" set. In other words, the first three years of historical monthly data are used to estimate and optimize any parameters and to initialize each method. Forecasts are then produced for the test set. This section discusses how each forecasting method was optimized and the cost function associated with all optimizations. For each forecasting technique, all applicable initialization values, smoothing parameters, and input variables are estimated to minimize a selected cost function. All generated forecasts are then compared and analyzed across the board. The table below presents an overview of the metric that was used to optimize each method.

Table 6. Forecasting Optimization Strategy



Forecasting Optimization Strategy	
Method	**Cost Function**
ARIMA	AICc
SMA	MASE
SES	MSE
CROSTON	MAR
SBA	MAR
TSB	MAR

Depending on the selection of error metric, forecasts can give diverse results. It may become unclear which forecast is the best and most applicable. Therefore, the selection of cost functions is crucial. All forecasts are generated using code in R statistical software.

ARIMA

The best forecast from ARIMA is based off of the lowest AICc between all the models. R code is written to produce 36 different ARIMA forecasts from the training dataset. Following the Box-Jenkins procedures, the R pseudo code is shown below,

```
For each Time Series i
    Split into 3-Year data
    Select a Box Cox transformation parameter if needed
    Forecasts = ARIMA(Time Series i, Horizon Forecast = 12, Autoregressive
    Order = 0:3, Differencing Order = 0:2, Moving Average Order = 0:3)
    Best Model = Forecasts(min AICc)
    Record Out of Sample Forecasts for best model
    Record Single Step In-Sample Forecasts for best model
    Record if Applicable(Forecasting Model Used, Smoothing Weights,
    Initialization Values)
Next
```

Figure 9. Pseudo R Code for ARIMA Optimization

By determining the minimum AICc, the best model is selected to represent an optimal ARIMA forecast.

SMA

For the simple moving average, MASE was the cost function of choice based on the advantages and recommendations of Hyndman [15]. The only parameter to be estimated for minimum MASE was the number of moving average periods. This number is constrained from 1 to 12 months in order to prevent going past a yearly moving average. So for each time series, the forecast with the minimum MASE was selected as the best forecast.

Croston’s Method, SBA, and TSB

Croston’s method and its variants are optimized based on a MAR cost function. It has been argued that these methods should not be interpreted simply as forecasted expected demand, but as a demand rate. To account for this difference in units, MAR was selected to prevent inappropriate comparisons. Kourentzes discusses in his paper the unstable behavior of using conventional error metrics as they often result in large smoothing parameters [34]. Furthermore, Kourentzes goes on assessing that when using these techniques traditional error metrics such as MAD and MSE tend to bias forecasts in favor of the zero-demand forecasts and lack practicality for inventory decisions. With this in mind, MAR is selected as the most applicable and appropriate cost function.

SES

SES forecasts are made based on MSE. While the benefit of using alternative cost functions such as MAR for Croston’s method and its variants have been shown, it was found that methods such as SES do not receive an increase in performance [34]. When optimizing the various exponential smoothing methods, minimizing the sum of squared errors is the standard practice [11].

Pseudo Code for Optimizing Forecasting Methods

Excluding the ARIMA method, below is the pseudo code used to optimize and produce forecasts for all other methods used in this study.

```
For each Forecasting Method
    For each Time Series i
        Forecast = Optimize Forecasting Method(Time Series i, h = Horizon
        Forecast (ex. h =12 Time Periods into the Future)
        Record Out of Sample Forecasts
        Record Single Step In-Sample Forecasts
        Record if Applicable(Forecasting Model Used, Smoothing Weights,
        Initialization Values, Moving Average Period)
    Next
Next
```

Figure 10 Pseudo R Code for Forecast Optimization

As seen in the figure 10 code, the resulting output from this step includes fitted single step in-sample forecasts from the first three years of the USTRANSCOM data and 1 year out of sample forecast. In addition, all other applicable factors such as smoothing weight, initialization values, and moving average periods are collected for analysis.

Summary

The methodology in this section consists of five essential steps: data organization, data exploration, selection of relevant forecasting methods, selection of relevant cost functions, and execution of automated forecasting code to optimize each forecast. Using the first three years of the organized historical data, forecasts are produced for one year while minimizing each associated cost function. In the next section, both in sample and out of sample forecast are analyzed based on specific accuracy metrics across each method.

IV. Analysis and Results

Chapter Overview

The methodology presented in the previous chapter is executed and produces in-sample and out-of-sample future forecasts for every method. This section now organizes the output and analyzes the significance of the results for future interpretation. The chapter is split into three main parts: initial out-of-sample results, ranking/comparing the forecasting methods based on appropriate error metrics, and a closer look into analyzing the optimal "hit rate percentage" of the presented methodology. Some limitations of the analysis are also discussed. For reduced repetition, from this point on all mentioned methods are considered the optimized version for each time series. For example, when SES is discussed in the results, the forecast method has been optimized with the best initial starting value and smoothing parameter. The findings presented in this section set the path for important conclusions and implications for this research problem.

Error Metrics for Overall Comparison

With forecasts for all presented methods applied, the analysis requires a strategy to compare performances across the board. As mentioned previously, depending on the error metric selected, the top forecasting method for one measurement may not be the best method for another metric. This study applied the standard MSE and MAD error metrics as they are the simplest and easiest to understand. Again, MSE calculations prevent positive and negative forecasts from cancelling each other out and give a greater penalty for larger deviations through the square property. Therefore, the quality of the forecasts should not be judged based on a single measure.

As an additional forecast measure, Periods in Stock (PIS) is used. Supply planners require a systematic way to interpret overstock and shortages from a forecast. PIS represents a complementary error measure that considers the time aspect of demand forecasts compared to actual demand. In this way, different aspects of a forecast can be observed. In their 2010 article, Wallstrom and Segerstedt [35] describe PIS as the total number of time periods a single unit of forecasted stock has been in or out of stock. This is calculated as:

$$\text{Periods in Stock} = PIS_n = -\sum_{i=1}^{n}\sum_{j=1}^{i}(y_j - \hat{y}_j) \qquad \textbf{(16)}$$

where:
n = total number of time periods forecasted
y_j = the actual demand at time period *j*
$\hat{y}_j$ = the forecasted demand at time period *j*

This calculation acts as a tacker on the cumulative error of the forecast through time. Like most of the other error metrics, a smaller number is preferred representing less bias. A positive number indicates the forecasting method is over estimating the demand while a negative number is a sign of underestimation or periods of shortage.

Initial Out-of-Sample Results

First, out-of-sample forecasts are observed to see future performance. To simply calculate the pure bias between forecast and actual demand, PIS is based on minimum absolute values. The best forecasting methods are counted and the percentage of time where each optimized technique is the top option for each metric is shown in Figures 11-13 below.

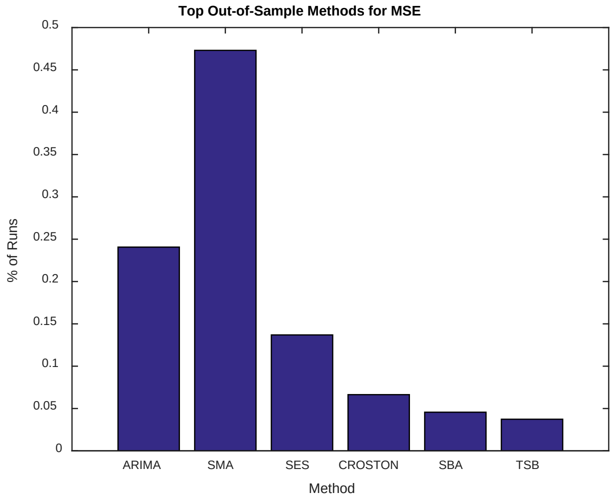


Figure 11. Top Out-of-Sample Methods for MSE

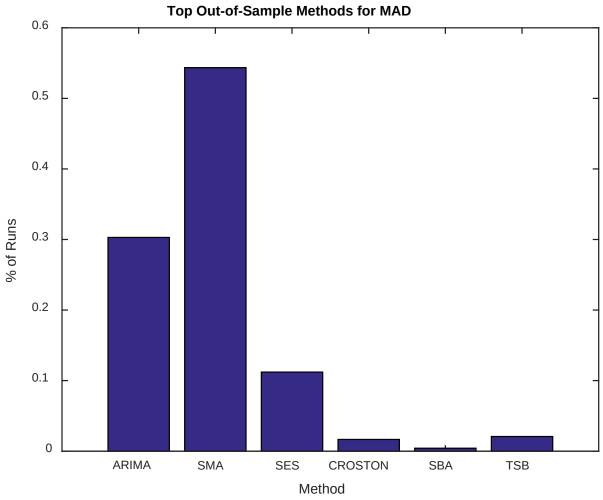


Figure 12. Top Out-of-Sample Methods for MAD

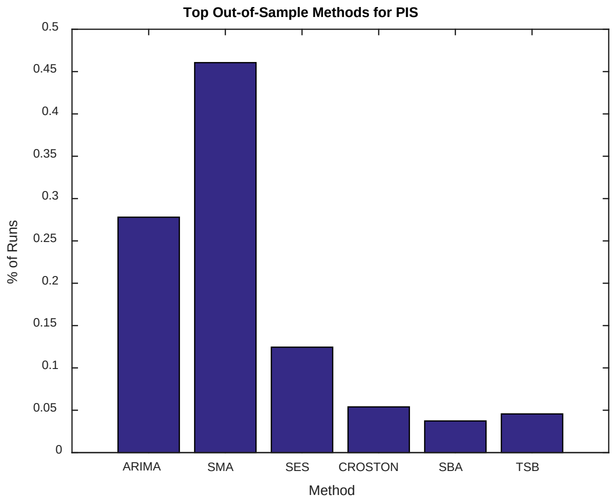


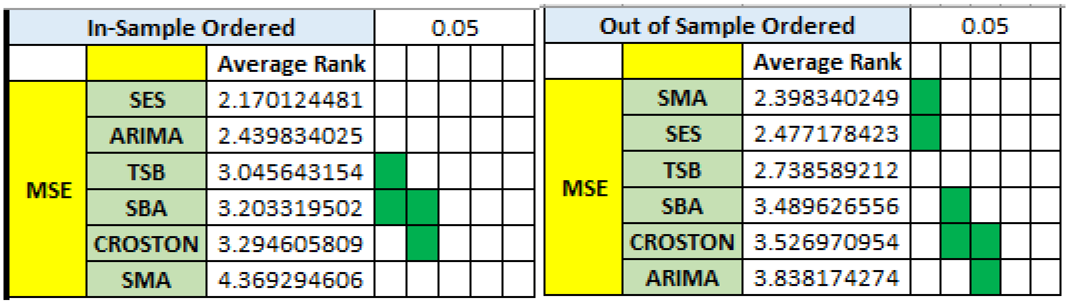
Figure 13. Top Out-of-Sample Methods for PIS

It should be noted, that there were a number of ties in error between the methods. In this case, the win is given to ARIMA as it is used as the baseline for improvement. While each metric showed slightly different results, all showed similar patterns. Based on all three metrics used, SMA produced the most accurate forecast almost half of the time. ARIMA and SES also had notable showings for this dataset. The Croston based methods rarely produced the most accurate forecast when compared to the other more basic methods.

Ranking the Methods

An overall assessment is conducted on the forecasting methods. The different error measures presented are used for all of the optimized forecasts and are organized for analysis. For each time series, the forecasting techniques were ranked for both the in-sample three year training dataset and out-of-sample one year testing set. Rankings for each error metric are then averaged and organized for investigation. Equal errors between methods are treated as equal rankings. Results are seen in Tables 7-8. Solid vertical marks between methods indicate statistical tests for 5% significance. Essentially, it marks when there is not enough evidence of significant difference between methods.

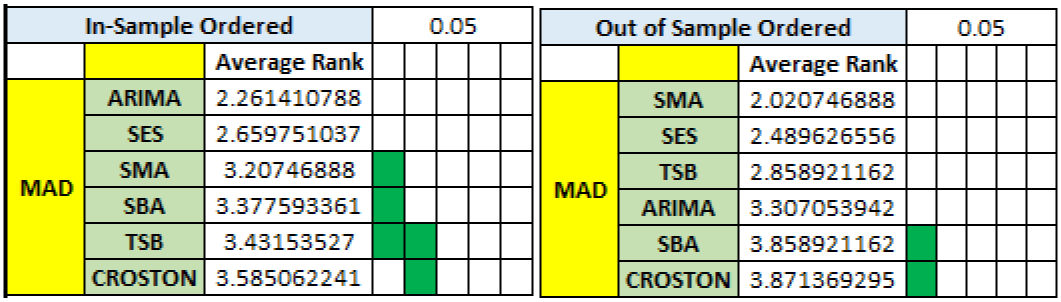
Table 7. In-Sample and Out-of-Sample MSE Rankings



In-Sample Ordered			0.05				
		Average Rank					
MSE	SES	2.170124481					
	ARIMA	2.439834025					
	TSB	3.045643154	🟩				
	SBA	3.203319502	🟩	🟩			
	CROSTON	3.294605809		🟩			
	SMA	4.369294606					

Out of Sample Ordered			0.05				
		Average Rank					
MSE	SMA	2.398340249	🟩				
	SES	2.477178423	🟩				
	TSB	2.738589212					
	SBA	3.489626556		🟩			
	CROSTON	3.526970954		🟩	🟩		
	ARIMA	3.838174274			🟩		

Table 8. In-Sample and Out-of-Sample MAD Rankings

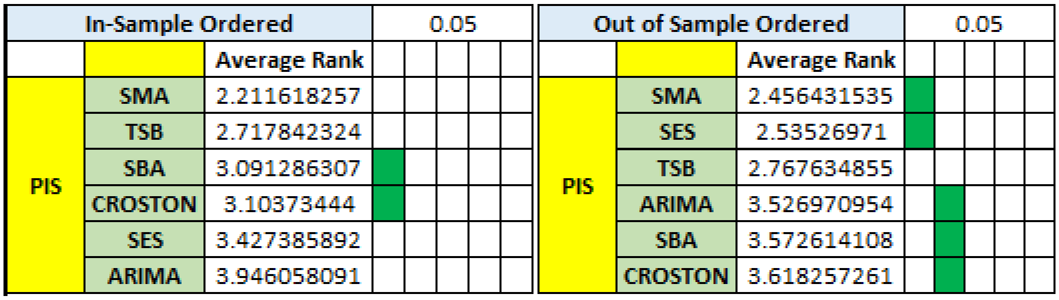


In-Sample Ordered			0.05				
		Average Rank					
MAD	ARIMA	2.261410788					
	SES	2.659751037					
	SMA	3.20746888	🟩				
	SBA	3.377593361	🟩				
	TSB	3.43153527	🟩	🟩			
	CROSTON	3.585062241		🟩			

Out of Sample Ordered			0.05				
		Average Rank					
MAD	SMA	2.020746888					
	SES	2.489626556					
	TSB	2.858921162					
	ARIMA	3.307053942					
	SBA	3.858921162	🟩				
	CROSTON	3.871369295	🟩				

In terms of MSE and MAD, ARIMA performs well with the in-sample training data. However, in these rankings it performs very poorly in the future out-of-sample dataset compared to the other methods. While both error metrics penalize deviations differently, the ranking results show similar patterns with SMA and SES jumping to the top for out-of-sample forecasts and ARIMA, SBA, CROSTON falling to the bottom. These rankings are further explored with the PIS analysis which adds another dimension to error analysis.

Table 9. In-Sample and Out-of-Sample PIS Rankings



In-Sample Ordered			0.05				
		Average Rank					
PIS	SMA	2.211618257					
	TSB	2.717842324					
	SBA	3.091286307	🟩				
	CROSTON	3.10373444	🟩				
	SES	3.427385892					
	ARIMA	3.946058091					

Out of Sample Ordered			0.05				
		Average Rank					
PIS	SMA	2.456431535	🟩				
	SES	2.53526971	🟩				
	TSB	2.767634855					
	ARIMA	3.526970954		🟩			
	SBA	3.572614108		🟩			
	CROSTON	3.618257261		🟩			

When observing the PIS results in Table 9, ARIMA's in-sample and out-of-sample forecasts both perform poorly. Again, SMA has the highest average forecast ranking for the out-of-sample testing set. Interestingly, when it came to PIS, SMA also performed the best in overall rankings for the in-sample dataset. In addition, SES makes an improvement from one dataset to the other.

In all of the rankings, SMA proved to be the best option for one year future forecasts with SES falling closely behind. This close competition between SMA and SES can be seen from the tests of significance. For both MSE and PIS, there was no evidence of a significant difference between the average rankings of the two methods. A noteworthy point in these results is the behavior of Croston's method and its variant SBA. While both methods tended to perform poorly in the overall rankings, SBA is always ranked higher than Croston's method. However, statistical tests show that there is never any significant difference. TSB is the most consistent of all the rankings as it always seemed to fall right in the middle of the pack.

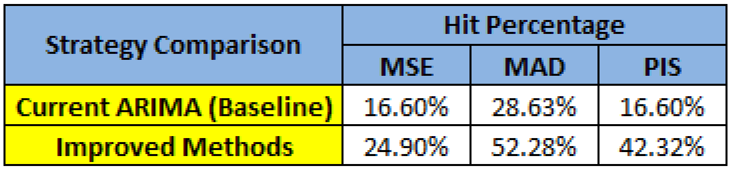
While these initial method rankings do provide valuable insight on forecasting precision, there are also sources for inaccuracy. When observing the forecasting errors one-by-one prior to ranking, many times each method's error measurement is often times extremely close. Therefore, simply placing a standard ranking on a method may be unnecessarily penalizing it when its performance is close to the best. This concept is explored further in the next section.

Analysis of Method Hit Percentage

As seen in the initial method rankings based on different error measures, the output showed mixed results between average in-sample rankings and out-of-sample rankings. In this portion of the analysis, the "hit percentage" between the training and testing datasets are further examined. Hit percentage is described as the following: based on the best forecasting method from the in-sample dataset, what percentage of the time is that method also the best forecasting method for the out-of-sample dataset?

Currently, USTRANSCOM utilizes an ARIMA optimizer to produce its rail demand forecasts based on AIC. This strategy is the baseline model for this study. This study explored additional methods designed for intermittent demand and cost functions to optimize forecasts. Table 10 presents the hit rate percentage comparison between the current ARIMA baseline and improved methods. The improved methods are simply the added usage of optimized SMA, SES, Croston's method, SBA, and TSB.

Table 10. ARIMA Baseline vs Improved Methods Hit Percentage Comparison



Strategy Comparison	Hit Percentage		
	MSE	MAD	PIS
Current ARIMA (Baseline)	16.60%	28.63%	16.60%
Improved Methods	24.90%	52.28%	42.32%

At first glance, there is some improvement in the hit rate between the current ARIMA baseline method and improved methods. For instance, using the improved method strategy by MSE provided a slight improvement increased the hit rate percentage to an underwhelming 24.90%. Despite the stronger rise in performance by MAD and PIS, the final hit rate percentages are still mediocre. However, the improvements still show promise in potential methods to improve hit rate accuracy. When it comes to automation and refining the forecast selection process, focusing on specific metrics may prove beneficial. This concept is explored further.

Hit Rate Analysis of Combined Scaled Errors

Analysis of method performance and error offer a basis in determining a pragmatic strategy for choosing forecasts. Each metric plays a unique role in overall prediction accuracy. These tactics are investigated further by ranking and examining the hit rates for combined scaled errors. This procedure is done to observe which metrics offer the most utility in optimizing hit rates and help decision makers elect the most advantageous method.

First, because the error metrics all have unique properties and scales, they must be normalized. For each time series, all errors are normalized using:

$$NormalizedError_{ij} = \frac{Error_{ij} - N_{ij}}{X_{ij} - N_{ij}} \quad \textbf{(17)}$$

where:

$Error_{ij}$ = the error value of metric *i* and time series *j*
N_{ij} = the minimum error value of metric *i* and time series *j*
X_{ij} = the maximum error value of metric *i* and time series *j*

Once normalized, weights for each error metric are calculated to solve for best in-sample and out of sample methods. Consequently, these weights also influence the highest hit rates for selecting the most appropriate methods. The formula for combined scaled errors is given here:

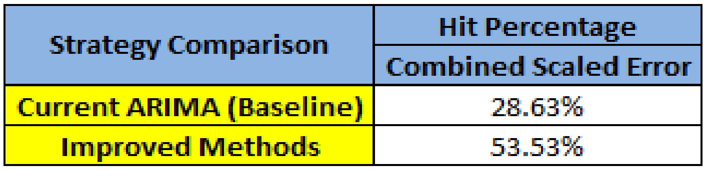
$$\text{Combined Scaled Error} = W_{MSE}Y_{MSE} + W_{MAD}Y_{MAD} + W_{PIS}Y_{PIS} \quad \textbf{(18)}$$

where:

$W_{MSE}, W_{MAD}, W_{PIS}$ = the weights given to the normalized errors of MSE, MAD, and PIS respectively
$Y_{MSE}, \mathrm{Y}_{MAD}, \mathrm{Y}_{PIS}$ = the normalized errors of MSE, MAD, and PIS respectively

Using these equations, it was determined that the optimal weights for the highest improved hit rates were $(W_{MSE}, W_{MAD}, W_{PIS})$ = (0, 0.86, 0.14). Here, every combination of weights summing to 1 was used. The actual comparison and improvement in hit rate is summarized in Table 11.

Table 11. ARIMA Baseline vs Improved Methods Hit Percentage Comparison Using Combined Scaled Errors



Strategy Comparison	Hit Percentage
	Combined Scaled Error
Current ARIMA (Baseline)	28.63%
Improved Methods	53.53%

Again, there is a major improvement from simply using the current baseline ARIMA optimizer to the combination with improved methods. The optimized weights also suggest that MAD is the most influential error metric when boosting hit rates. This error metric carries the most weight in selecting the most appropriate method for future forecasts. PIS also holds some value. Method rankings for the combined scaled errors were also conducted for thorough analysis and can be found in Appendix B.

Summary

Considering and optimizing proposed methods for forecasting lumpy intermittent train demand shows potential for improved performance compared to current forecasting procedures used by USTRANSCOM. The outputted forecasts in this study were analyzed and ranked across the board using three different error metrics complementing each other. Although the study shows mixed results, optimizing traditional methods such as SMA and SES produced the best forecasts. While ARIMA demonstrated strong rankings with some of the historical in-sample data, it performed poorly when predicting future demand. However, depending on the allowable error, slightly biased forecasts may not be so different. The initial results suggest that the optimized ARIMA is still a valuable option for future predictions but, receives an extra boost with the consideration of other methods. Using this improved mix of optimized methods does provide notable improvement from the current baseline ARIMA optimizer in terms of MAD and PIS. Lastly, it was found that popular techniques designed specifically for lumpy demand such as Croston's method and its variant SBA, are inappropriate for USTRANSCOM's railcar demand.

Despite the varied results, the optimization of techniques included in this study can help rail freight managers make better use of their historical data and produce improved forecasting results. The hit rate percentage analysis presented in this analysis is another tool for planners to gauge the risk in selecting certain methods and metrics. It was seen that utilizing MAD as the error metric of choice can assist in maximizing hit rates and selecting most applicable methods. Furthermore, findings show improvement from current baseline strategies. With the insight found in this study, conclusions and recommendations can be made to ensure that decision makers deal with railcar demands and operations more efficiently. Further significance and impacts on forecasting intermittent railcar demands are discussed further in the next chapter.

V. Conclusions and Recommendations

Chapter Overview

Delivering accurate and timely rail freight demands forecasts is an extremely challenging task for organizations. This chapter wraps up the major points made in this study. After framing the complex problem, proposing a methodology, and analyzing the results, conclusions and recommendations are made. Findings are summarized and significance to the problem is explained. Essentially, the impact and application to this field from this investigation are discussed. In addition, recommendations on future actions and possible paths for subsequent research are introduced.

Conclusions and Significance

The primary objective of this research is to apply a number of forecasting methods designed for intermittent demand and to investigate the behavior of these methods for practical use for USTRANSCOM's rail freight demands. A number of conclusions are drawn from this study and are discussed in this section. Forecasting irregular and sparse time series demand is a complex and challenging task. Intermittent arrivals of demand result in increased stock levels and biased future estimates. To properly address these issues, selection of forecasting methods has a vital impact on an organization's overall performance. Most importantly, the main purpose of forecasting is to cost-efficiently prepare planners with short and precise demand times. The optimization of methods takes managers one step closer towards increasing value and efficiency.

After the chosen dataset is split and organized by railcar commodity and location, it is clear that the data is extremely sparse and intermittent. The time series' show frequent periods of zero demand and month to month variability. The level of lumpiness in this dataset causes unique issues for forecasts when compared to literature, even with techniques designed specifically to mitigate these characteristics.

Again the perceived performance of a forecasting method is dependent on error measurements and type of data. Different measurements of error will usually favor different methods. Forecast error is merely an instrument to help decision makers make comparisons. The most commonly used measures are MAD and MSE. However, these standard measures are not themselves sufficient for a comprehensive study. Therefore also using PIS adds another dimension to this analysis. In the end, hit rate analysis suggests MAD to be the most valuable in determining future forecasts. While MASE is a very useful and robust accuracy metric, it runs into issues with this specific dataset because of extended and frequent periods of zero demand. The only situation where MASE is infinite or undefined is when all historical observations are equal. Unfortunately, this is the case for many of the testing/validation datasets.

From the results and analysis, it is clear that SMA compares very favorably with the various popular smoothing methods. It shows robust performance even with the presence of outliers which occur frequently and at a large scale. SES also performs surprisingly well compared to the more complex techniques. In addition, analysis suggests SBA clearly out performs Croston's method in every metric. When it comes to extremely sparse intermittent demand, the original Croston's method has been known to have a positive bias.

With the knowledge gathered from this study, USTRANSCOM will have a better foundation for making organizational decisions on where railcars are required. Having this toolset for more forecasting options leads to more accurate and informed forecasts. The hit-rate analysis in this study also allows decision makers to assess the risk in choosing specific forecasts and ignoring certain errors. Next, specific recommendations are presented to reiterate these impacts.

Recommendations

The current optimized ARIMA technique used by USTRANSCOM is valuable for its versatility but should not be the only strategy considered. Contrary to some literature, optimizing traditional elementary methods such as SMA and SES are worthwhile when forecasting highly sparse railcar demands. Because of the nature of this datasets, these methods better handle the data without becoming overly complicated. Despite the theoretical superiority of Croston's method and its variants, the analysis suggests only modest gains in utility when compared to some of the other simpler techniques. Croston's method performs very poorly in all aspects of this study and should only be used for research purposes. It would be disadvantageous to use the method in a practical setting. Unbiased variants of Croston's method such as SBA and TSB almost always produce more accurate forecasts.

In regards to how forecasters should measure accuracy, using MAD showed the greatest improvements for selecting future methods and increasing the hit rate. Each metric has its own properties. But while other metrics have unique features and offer value in understanding the complete picture of accuracy, making decisions based on MAD leads to the greatest potential for improved results.

Future Research

This study is a first attempt at exploring practical strategies to assist USTRANSCOM's rail planning and operations. Adding a cost dimension to this research would be the next ideal step. By adding real and timely data on shipment costs, operation costs, and holding costs insights can be made on budget efficiency. Having supporting analysis on expenditures and savings for these forecasts would be an invaluable tool for planners.

There is a vast amount of ongoing research for forecasting intermittent demands. In this study, methods were optimized based on pre-determined cost functions. There is still much to learn in the forecast optimization field. Optimizing methods of various metrics and observing performance and behavior is a worthwhile process. A number of more modern and evolving forecasting methods exist such as neural networks. Additionally, further classifying and categorizing time series data and determining a forecasting strategy to deal with each type is another task for the future. In this study, time series were classified using a strategy from literature. However, methods and rankings were calculated across all forecasts. Therefore it is difficult to say which method is best suited for which type of demand. Classification and categorization of demand data has great potential for more advanced methods and future research.

Appendix

APPENDIX A

Type of Railcar Equipment Code:

RAILROAD

Box, automobile	KA
Box, damage prevention type	KP
Box, end door	KE
Box, any other type not over 52'6"	KO1
over 52'6", but not over 60'9"	KO2
over 60'9"	KO3
Box, missile, DODX w/refrigeration	KX
Box, nuclear waste, DODX w/racks permanently affixed	KC
Caboose, DODX armed guard	KU
Flat, bilevel, not enclosed	KB1
enclosed	KB2
Flat, trilevel, not enclosed	KL1
enclosed	KL2
Flat heavy duty	KY
Flat, any other type not over 70 ft., includes DODX 41000-series cars	KF1
over 70 ft, but not over 90 ft., includes DODX 42000-series cars	KF2
Flat, DODX, not over 60 ft	KZ1
over 60 ft., includes DODX 40000-series cars	KZ2
Locomotive, under own power, on own wheels	KZ3
Locomotive, n/u/own power, on own wheels	KZ4
Locomotive, n/u/own power, n/on own wheel	KZ5
Gondola, drop ends	KD
Gondola, any other type 52 ft, high capacity	KG1
65 ft, high capacity	KG2
Hopper:	
open-top, 80 tons and less	KH1
open-top, 100 tons, 2,000 cubic feet	KH2
closed-top, 70 tons, 2,000 cubic feet	KH3
closed-top, 100 tons, 2,929 cubic feet	KH4
closed-top, 100 tons, 4,000 cubic feet	KH5
closed-top, 100 tons, 4,600 cubic feet	KH6
Refrigerator, perishable foods, not over 53 ft. mechanical	KK1
over 53 ft, but not over 61 ft. mechanical	KK2
Refrigerator, any other type, not over 53 ft. mechanical	KR1
over 53 ft, but not over 65 ft. mechanical	KR2
Stock	KS
Tank, 10,000 gallons	KT1
Tank, 20,000 gallons	KT2
Tank, 30,000 gallons	KT3
TOFC car	KW1
COFC car, includes DODX 48000-series cars	KW2

APPENDIX B

In-Sample and Out-of-Sample PIS Rankings:

In-Sample Ordered				0.05				
	Method	Average Rank	Overall Rank					
Scaled Error	ARIMA	2.270	1					
	SES	2.714	2					
	SMA	3.170	3	🟩				
	SBA	3.398	4	🟩				
	TSB	3.398	4	🟩	🟩			
	CROSTON	3.560	6		🟩			

Out of Sample Ordered				0.05				
	Method	Average Rank	Overall Rank					
Scaled Error	SMA	2.066	1					
	SES	2.494	2					
	TSB	2.876	3					
	ARIMA	3.299	4					
	SBA	3.784	5	🟩				
	CROSTON	3.834	6	🟩				

APPENDIX C

R Code for Fitted and Future ARIMA Forecasts:

```
# 1. Load packages
library("zoo", lib.loc=NULL)
library("timeDate", lib.loc=NULL)
library("Rcpp", lib.loc=NULL)
library("fracdiff", lib.loc=NULL)
library("quadprog", lib.loc=NULL)
library("colorspace", lib.loc=NULL)
library("forecast", lib.loc=NULL)
library("MASS", lib.loc=NULL)

# 2. User-specified inputs
B <- read.csv("C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/traindata_historical_11to13.csv", header=TRUE) #  UPDATE FILE
LOCATION.  IF USING COPY/PASTE, MAKE SURE TO CHANGE "\" TO "/"
A.periodicity <- 12 #  INDICATE PERIOD (WHETHER DATA IS DAILY (365), WEEKLY
(52), MONTHLY (12), OR QUARTERLY (4))
numheads <- 1 #  INDICATE HOW MANY _COLUMNS_ OF "HEADER DATA" ARE ON
THE SHEET BEFORE THE DATA
numobs <- 36 #  INDICATE HOW MANY OBSERVATIONS FOR EACH CATEGORY ARE
CONTAINED IN THE ORIGINAL DATA SET
numforecast <- 12 #  INDICATE HOW MANY PERIODS TO FORECAST (NUMFORECAST /
PERIODICITY = # YEARS FORECASTED)
numhist <- 3 #  INDICATE HOW MANY YEARS OF DATA ARE IN THE ORIGINAL
DATASET

# 3. Set up the matrix that will hold the forecasts
A <- data.frame(B)
forecastmatrix <- matrix(0, numforecast, ncol(A))
results <-data.frame(forecastmatrix)
methods <- matrix("Zeros", 2, ncol(A))
fitList <- list() #this will hold a list of the fitted values

A.cs <- colSums(A !=0)


# 4. Loop that will bring in each column of data and make it a time-series dataset
for (i in (1 + numheads) : ncol(A))
{
  A.ts <- ts(A[[i]], freq = A.periodicity)


    # 5. Apply a Box-Cox (variance-stabilizing) Transform, if needed
    lamval3 <- BoxCox.lambda(A.ts, method=c("guerrero","loglik"), lower=-1, upper=2)

    # 6. Fit multiple models using ARIMA and ETS
```

```
   fit3 <- auto.arima(A.ts, max.p=3, max.q=3, max.P=3, max.Q=3, max.order=10, max.d=2,
max.D=2, lambda=lamval3,
                    ic=c("aicc", "aic", "bic"), test=c("kpss")) #checks all of these ARIMA models!


    fitcast3 <- forecast(fit3, h=numforecast)
    results[,i] <- fitcast3$mean
    methods[1,i] <- fitcast3$method
    methods[2,i] <- 3
    fitList[i] <- list(fitted(forecast(fitcast3)))

} #end of loop

fitted_values <- do.call(rbind,fitList)

write.csv(fitted_values, file = "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/ARIMA_ALL_fitted.csv")
write.csv(results, file = "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/ARIMA_ALL_results.csv")
write.csv(methods, file =  "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/ARIMA_ALL_methods.csv")
```

R Code for Fitted and Future SES Forecasts:

```
# 1. Load packages
library("zoo", lib.loc=NULL)
library("timeDate", lib.loc=NULL)
library("Rcpp", lib.loc=NULL)
library("fracdiff", lib.loc=NULL)
library("quadprog", lib.loc=NULL)
library("colorspace", lib.loc=NULL)
library("forecast", lib.loc=NULL)
library("MASS", lib.loc=NULL)
library("tsintermittent", lib.loc=NULL)

# 2. User-specified inputs
B <- read.csv("C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/traindata_historical_11to13.csv", header=TRUE) #  UPDATE FILE
LOCATION.  IF USING COPY/PASTE, MAKE SURE TO CHANGE "\" TO "/"
A.periodicity <- 12 #  INDICATE PERIOD (WHETHER DATA IS DAILY (365), WEEKLY
(52), MONTHLY (12), OR QUARTERLY (4))
numheads <- 1 #  INDICATE HOW MANY _COLUMNS_ OF "HEADER DATA" ARE ON
THE SHEET BEFORE THE DATA
numobs <- 36 #  INDICATE HOW MANY OBSERVATIONS FOR EACH CATEGORY ARE
CONTAINED IN THE ORIGINAL DATA SET
numforecast <- 12 #  INDICATE HOW MANY PERIODS TO FORECAST (NUMFORECAST /
PERIODICITY = # YEARS FORECASTED)
```

```
numhist <- 3 #  INDICATE HOW MANY YEARS OF DATA ARE IN THE ORIGINAL
DATASET

# 3. Set up the matrix that will hold the forecasts
A <- data.frame(B)
forecastmatrix <- matrix(0, numforecast, ncol(A))
results <-data.frame(forecastmatrix)
methods <- matrix("Zeros", 3, ncol(A))
fitList <- data.frame(matrix("NA", numobs, ncol(A))) #this will hold the fitted values


# 4. Loop that will bring in each column of data and make it a time-series dataset
for (i in (1 + numheads) : ncol(A))
{
 A.ts <- ts(A[i])


   # 6. Fit models using SES
   fit3 <- sexsm(A.ts, h=numforecast, w=NULL, cost = "MSE") #simple exponential smoothing
with optimal parameters. MSE cost function used for optimization

   results[,i] <- fit3$frc.out #out of sample forecasts
   fitList[,i] <- fit3$frc.in #single step in sample forecasts
   methods[1,i] <- fit3$model #model used
   methods[2,i] <- fit3$alpha #smoothing parameter alpha
   methods[3,i] <- fit3$initial #initial value used

} #end of loop


write.csv(fitList, file = "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/SES_fitted.csv")
write.csv(results, file = "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/SES_results.csv")
write.csv(methods, file =  "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/SES_methods.csv")
```

R Code for Fitted and Future CROSTON Forecasts:

```
# 1. Load packages
library("zoo", lib.loc=NULL)
library("timeDate", lib.loc=NULL)
library("Rcpp", lib.loc=NULL)
library("fracdiff", lib.loc=NULL)
library("quadprog", lib.loc=NULL)
library("colorspace", lib.loc=NULL)
library("forecast", lib.loc=NULL)
library("MASS", lib.loc=NULL)
```

```
library("tsintermittent", lib.loc=NULL)

# 2. User-specified inputs
B <- read.csv("C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/traindata_historical_11to13.csv", header=TRUE) #  UPDATE FILE
LOCATION.  IF USING COPY/PASTE, MAKE SURE TO CHANGE "\" TO "/"
A.periodicity <- 12 #  INDICATE PERIOD (WHETHER DATA IS DAILY (365), WEEKLY
(52), MONTHLY (12), OR QUARTERLY (4))
numheads <- 1 #  INDICATE HOW MANY _COLUMNS_ OF "HEADER DATA" ARE ON
THE SHEET BEFORE THE DATA
numobs <- 36 #  INDICATE HOW MANY OBSERVATIONS FOR EACH CATEGORY ARE
CONTAINED IN THE ORIGINAL DATA SET
numforecast <- 15 #  INDICATE HOW MANY PERIODS TO FORECAST (NUMFORECAST /
PERIODICITY = # YEARS FORECASTED)
numhist <- 3 #  INDICATE HOW MANY YEARS OF DATA ARE IN THE ORIGINAL
DATASET

# 3. Set up the matrix that will hold the forecasts
A <- data.frame(B)
forecastmatrix <- matrix(0, numforecast, ncol(A))
results <-data.frame(forecastmatrix)
methods <- matrix("Zeros", 5, ncol(A))
fitList <- data.frame(matrix("NA", numobs, ncol(A))) #this will hold the fitted values

A.cs <- colSums(A !=0)


# 4. Loop that will bring in each column of data and make it a time-series dataset
for (i in (1 + numheads) : ncol(A))
{
 A.ts <- ts(A[i])

  # 6. Fit models using CROSTON
 if ((A.cs[i]) %in% c(0,1)) #use this if there are less than 2 nonzero demands in time series. Uses
alpha 0.1 as default
  {fit3 <- croston(A.ts, h=numforecast, alpha=0.1)
  results[,i] <- fit3$mean #out of sample forecasts
  fitList[,i] <- fit3$fitted #single step in sample forecasts
  methods[1,i] <- fit3$method #model used
  methods[2,i] <- 0.1 #smoothing weight for demand
  methods[3,i] <- 0.1 #smoothing weight for demand
  methods[4,i] <- 0 #initial value used for demand
  methods[5,i] <- 0 #initial value used for demand

 } else{

  fit3 <- crost(A.ts, h=numforecast, w=NULL) #crostons method with optimal parameters. MAR
is default cost function for optimization
```

```
    results[,i] <- fit3$frc.out #out of sample forecasts
    fitList[,i] <- fit3$frc.in #single step in sample forecasts
    methods[1,i] <- fit3$model #model used
    methods[2,i] <- fit3$weights[1] #smoothing weight for demand
    methods[3,i] <- fit3$weights[2] #smoothing weight for intervals
    methods[4,i] <- fit3$initial[1] #initial value used for demand
    methods[5,i] <- fit3$initial[2] #initial value used for demand
  }
} #end of loop


write.csv(fitList, file = "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/CROSTON_fitted.csv")
write.csv(results, file = "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/CROSTON_results.csv")
write.csv(methods, file =  "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/CROSTON_methods.csv")
```

R Code for Fitted and Future SBA Forecasts:

```
# 1. Load packages
library("zoo", lib.loc=NULL)
library("timeDate", lib.loc=NULL)
library("Rcpp", lib.loc=NULL)
library("fracdiff", lib.loc=NULL)
library("quadprog", lib.loc=NULL)
library("colorspace", lib.loc=NULL)
library("forecast", lib.loc=NULL)
library("MASS", lib.loc=NULL)
library("tsintermittent", lib.loc=NULL)

# 2. User-specified inputs
B <- read.csv("C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/traindata_historical_11to13.csv", header=TRUE) #  UPDATE FILE
LOCATION.  IF USING COPY/PASTE, MAKE SURE TO CHANGE "\" TO "/"
A.periodicity <- 12 #  INDICATE PERIOD (WHETHER DATA IS DAILY (365), WEEKLY
(52), MONTHLY (12), OR QUARTERLY (4))
numheads <- 1 #  INDICATE HOW MANY _COLUMNS_ OF "HEADER DATA" ARE ON
THE SHEET BEFORE THE DATA
numobs <- 36 #  INDICATE HOW MANY OBSERVATIONS FOR EACH CATEGORY ARE
CONTAINED IN THE ORIGINAL DATA SET
numforecast <- 15 #  INDICATE HOW MANY PERIODS TO FORECAST (NUMFORECAST /
PERIODICITY = # YEARS FORECASTED)
numhist <- 3 #  INDICATE HOW MANY YEARS OF DATA ARE IN THE ORIGINAL
DATASET

# 3. Set up the matrix that will hold the forecasts
A <- data.frame(B)
forecastmatrix <- matrix(0, numforecast, ncol(A))
```

```
results <-data.frame(forecastmatrix)
methods <- matrix("Zeros", 5, ncol(A))
fitList <- data.frame(matrix("NA", numobs, ncol(A))) #this will hold the fitted values

A.cs <- colSums(A !=0)


# 4. Loop that will bring in each column of data and make it a time-series dataset
for (i in (1 + numheads) : ncol(A))
{
 A.ts <- ts(A[i])

   # 6. Fit models using SBA
 if ((A.cs[i]) %in% c(0,1)) #use this if there are less than 2 nonzero demands in time series. Uses
alpha 0.1 as default
   {fit3 <- croston(A.ts, h=numforecast, alpha=0.1)
   results[,i] <- fit3$mean #out of sample forecasts
   fitList[,i] <- fit3$fitted #single step in sample forecasts
   methods[1,i] <- fit3$method #model used
   methods[2,i] <- 0.1 #smoothing weight for demand
   methods[3,i] <- 0.1 #smoothing weight for demand
   methods[4,i] <- 0 #initial value used for demand
   methods[5,i] <- 0 #initial value used for demand

 } else{

   fit3 <- crost(A.ts, h=numforecast, w=NULL, type="sba") #SBA method with optimal
parameters. MAR is default cost function for optimization

   results[,i] <- fit3$frc.out #out of sample forecasts
   fitList[,i] <- fit3$frc.in #single step in sample forecasts
   methods[1,i] <- fit3$model #model used
   methods[2,i] <- fit3$weights[1] #smoothing weight for demand
   methods[3,i] <- fit3$weights[2] #smoothing weight for intervals
   methods[4,i] <- fit3$initial[1] #initial value used for demand
   methods[5,i] <- fit3$initial[2] #initial value used for demand
 }
} #end of loop


write.csv(fitList, file = "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/SBA_fitted.csv")
write.csv(results, file = "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/SBA_results.csv")
write.csv(methods, file =  "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/SBA_methods.csv")
```

R Code for Fitted and Future TSB Forecasts:

```
# 1. Load packages
library("zoo", lib.loc=NULL)
library("timeDate", lib.loc=NULL)
library("Rcpp", lib.loc=NULL)
library("fracdiff", lib.loc=NULL)
library("quadprog", lib.loc=NULL)
library("colorspace", lib.loc=NULL)
library("forecast", lib.loc=NULL)
library("MASS", lib.loc=NULL)
library("tsintermittent", lib.loc=NULL)

# 2. User-specified inputs
B <- read.csv("C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/traindata_historical_11to13.csv", header=TRUE) #  UPDATE FILE
LOCATION.  IF USING COPY/PASTE, MAKE SURE TO CHANGE "\" TO "/"
A.periodicity <- 12 #  INDICATE PERIOD (WHETHER DATA IS DAILY (365), WEEKLY
(52), MONTHLY (12), OR QUARTERLY (4))
numheads <- 1 #  INDICATE HOW MANY _COLUMNS_ OF "HEADER DATA" ARE ON
THE SHEET BEFORE THE DATA
numobs <- 36 #  INDICATE HOW MANY OBSERVATIONS FOR EACH CATEGORY ARE
CONTAINED IN THE ORIGINAL DATA SET
numforecast <- 12 #  INDICATE HOW MANY PERIODS TO FORECAST (NUMFORECAST /
PERIODICITY = # YEARS FORECASTED)
numhist <- 3 #  INDICATE HOW MANY YEARS OF DATA ARE IN THE ORIGINAL
DATASET

# 3. Set up the matrix that will hold the forecasts
A <- data.frame(B)
forecastmatrix <- matrix(0, numforecast, ncol(A))
results <-data.frame(forecastmatrix)
methods <- matrix("Zeros", 5, ncol(A))
fitList <- data.frame(matrix("NA", numobs, ncol(A))) #this will hold the fitted values

A.cs <- colSums(A !=0)


# 4. Loop that will bring in each column of data and make it a time-series dataset
for (i in (1 + numheads) : ncol(A))
{
  A.ts <- ts(A[i])

    # 6. Fit models using CROSTON
  if ((A.cs[i]) %in% c(0)) #use this if there are less than 1 nonzero demands in time series. Uses
alpha 0.1 as default
    {fit3 <- croston(A.ts, h=numforecast, alpha=0.1)
    results[,i] <- fit3$mean #out of sample forecasts
    fitList[,i] <- fit3$fitted #single step in sample forecasts
```

```
    methods[1,i] <- fit3$method #model used
    methods[2,i] <- 0.1 #smoothing weight for demand
    methods[3,i] <- 0.1 #smoothing weight for intervals
    methods[4,i] <- 0 #initial value used for demand
    methods[5,i] <- 0 #initial value used for intervals

  } else{

    fit3 <- tsb(A.ts, h=numforecast, w=NULL) #tsb with optimal parameters. MAR is default cost
function for optimization

    results[,i] <- fit3$frc.out #out of sample forecasts
    fitList[,i] <- fit3$frc.in #single step in sample forecasts
    methods[1,i] <- fit3$model #model used
    methods[2,i] <- fit3$weights[1] #smoothing weight for demand
    methods[3,i] <- fit3$weights[2] #smoothing weight for intervals
    methods[4,i] <- fit3$initial[1] #initial value used for demand
    methods[5,i] <- fit3$initial[2] #initial value used for intervals
  }
} #end of loop


write.csv(fitList, file = "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/TSB_fitted.csv")
write.csv(results, file = "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/TSB_results.csv")
write.csv(methods, file =  "C:/Users/JPark/Documents/AFIT/AFIT Thesis
Docs/Methodology/OUTPUT/TSB_methods.csv")
```

APPENDIX D

USTRANSCOM Rail Freight Demand Data:

Each column represents a unique time series. The first number indicates location and the second number represents railcar commodity. Ex. 16.1 = Boise, ID (16) KF1 (1).

Subsequent tables use the same dates as the rows on this page

	1.2	1.7	2.7	3.7	4.2	4.4	4.7	5.7	6.2	6.7	7.7	8.6	8.7	9.7	10.2	10.7
Jan-11	0	0	0	0	0	61	10	0	0	0	5	0	0	0	0	0
Feb-11	0	0	0	0	0	0	12	0	0	0	0	0	0	1	1	0
Mar-11	0	0	0	0	0	0	32	0	12	3	0	0	0	0	0	0
Apr-11	0	0	0	0	0	0	73	0	0	0	0	0	0	0	0	0
May-11	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0
Jun-11	0	0	0	0	0	0	74	0	0	0	0	0	0	0	0	0
Jul-11	0	0	0	0	0	0	68	0	0	0	0	0	4	1	0	0
Aug-11	0	0	0	0	0	2	83	0	0	0	0	0	0	0	1	0
Sep-11	0	0	0	0	0	3	55	0	0	0	0	0	0	0	0	0
Oct-11	0	0	0	0	0	2	36	0	0	0	0	0	0	0	0	0
Nov-11	0	0	0	0	0	2	36	0	0	0	0	0	0	0	0	0
Dec-11	2	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0
Jan-12	0	0	0	0	0	0	40	0	0	14	0	0	0	0	0	15
Feb-12	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0
Mar-12	0	0	0	0	0	0	16	0	0	0	0	0	0	1	0	0
Apr-12	0	0	8	0	0	0	14	0	0	0	0	0	0	0	0	0
May-12	0	0	0	0	0	0	32	1	0	0	0	0	0	0	0	0
Jun-12	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0
Jul-12	0	0	0	0	0	0	13	0	0	0	0	0	0	1	0	0
Aug-12	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0
Sep-12	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0
Oct-12	0	0	0	0	0	0	3	0	0	0	0	0	0	1	0	0
Nov-12	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0
Dec-12	0	0	0	11	0	0	10	0	0	0	0	0	0	0	0	0
Jan-13	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0
Feb-13	0	5	0	0	0	0	4	0	0	0	0	0	0	0	0	0
Mar-13	0	4	0	0	0	0	8	0	0	0	0	0	0	1	0	0
Apr-13	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0
May-13	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0	0
Jun-13	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0
Jul-13	0	0	0	0	0	0	1	3	0	0	0	0	0	0	0	0
Aug-13	0	0	0	0	0	0	10	10	0	0	0	0	0	0	0	0
Sep-13	0	0	0	0	7	0	27	0	0	0	0	0	0	1	0	0
Oct-13	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0
Nov-13	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
Dec-13	0	0	0	0	0	0	24	0	0	0	0	0	0	0	0	0
Jan-14	0	0	0	0	0	0	15	0	0	0	0	8	0	1	0	0
Feb-14	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0
Mar-14	0	0	0	0	0	0	31	0	0	0	0	0	0	0	0	0
Apr-14	0	3	0	0	0	0	19	17	0	0	0	0	0	0	0	0
May-14	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0
Jun-14	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0
Jul-14	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0
Aug-14	0	0	0	0	0	0	54	13	0	0	0	0	0	0	1	0
Sep-14	0	3	0	0	0	0	26	0	0	0	0	0	0	0	0	0
Oct-14	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0	0
Nov-14	0	0	0	0	0	0	8	0	0	0	0	0	0	2	0	0
Dec-14	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0

11.1	**11.2**	**11.3**	**11.4**	**11.6**	**11.7**	**11.4**	**12.7**	**13.7**	**14.2**	**14.6**	**14.7**	**15.7**	**16.1**	**16.2**
0	66	0	0	0	20	0	0	0	0	0	0	0	0	0
2	120	0	0	0	105	0	0	0	0	0	0	0	0	0
13	89	0	4	0	51	0	0	0	0	0	0	0	0	0
0	23	0	1	0	39	2	0	0	0	0	0	0	0	0
5	19	2	7	0	21	1	0	0	0	0	0	0	0	0
0	12	0	0	0	33	0	0	0	0	0	0	0	0	0
2	88	0	0	0	126	0	0	0	0	0	0	0	0	0
0	16	0	0	0	94	1	0	0	0	0	0	0	0	0
1	14	0	0	0	65	2	0	0	10	0	0	0	0	0
2	57	0	0	0	77	0	0	0	0	0	0	0	0	0
3	15	0	0	0	44	0	0	0	0	0	0	0	0	0
9	74	0	0	13	173	0	0	0	0	0	0	0	0	0
10	127	0	6	0	125	0	0	0	0	0	0	0	0	0
6	215	0	0	0	165	0	0	0	0	0	0	0	0	0
13	251	0	15	0	243	0	0	0	0	0	0	0	0	0
28	113	0	17	0	187	0	0	5	0	0	0	0	0	0
16	175	0	31	0	199	0	0	0	0	0	0	0	0	0
31	123	0	0	0	154	0	0	0	0	0	0	0	0	0
55	127	0	0	0	190	1	0	0	0	0	0	0	0	15
20	207	0	0	0	268	0	0	0	0	0	0	0	0	0
7	10	0	4	0	168	0	0	0	0	0	0	0	0	0
1	17	0	0	0	124	2	0	0	0	0	0	0	0	27
6	75	0	8	0	132	1	0	0	0	0	0	0	0	0
17	137	0	0	0	140	0	0	0	0	0	0	0	0	0
9	130	0	0	0	156	0	0	0	0	0	0	0	0	0
5	30	0	0	0	65	0	0	0	0	0	0	0	0	0
0	33	0	5	0	154	0	0	0	0	0	0	0	0	0
1	48	0	0	0	148	1	0	0	0	0	0	0	0	0
2	23	0	3	0	111	1	22	0	0	0	0	0	0	0
4	39	0	0	0	118	2	0	0	0	0	0	33	0	0
1	58	0	0	0	52	2	0	0	0	0	0	0	0	0
2	38	0	6	0	98	1	0	0	0	0	0	0	0	0
1	38	0	37	0	68	1	0	0	0	0	0	0	14	0
14	140	0	0	0	230	2	0	0	0	0	0	0	0	0
1	49	0	0	0	170	0	0	0	0	0	0	0	0	0
0	23	0	0	0	126	0	0	0	0	0	0	0	0	0
0	87	0	0	0	79	0	0	0	0	0	0	0	0	0
2	103	0	0	0	101	0	0	0	0	0	0	0	0	0
6	105	0	0	0	98	0	0	0	0	0	0	0	0	0
6	119	0	0	0	77	1	0	0	0	12	0	0	0	0
0	47	0	0	0	36	0	0	0	0	0	0	0	0	0
1	135	0	0	0	81	1	0	0	1	0	0	0	0	0
0	100	0	0	0	86	2	0	0	0	0	0	0	0	0
1	85	0	0	0	72	0	0	0	0	0	34	0	48	0
0	55	0	0	0	55	0	0	0	0	0	0	0	0	3
0	153	0	0	0	89	2	0	0	0	0	0	0	0	0
0	75	0	0	0	63	0	0	0	0	0	0	0	0	0
0	64	0	0	0	17	0	0	0	0	0	0	0	0	0

16.6	16.7	17.7	18.1	18.2	18.5	18.6	18.7	19.7	20.6	20.7	21.7	22.4	22.7	23.7
0	0	0	0	2	0	0	0	0	0	0	0	0	0	0
0	4	0	0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	0	5	0	0	0	0	0	1	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	6	0	1	1	13	7	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	1	0	0	0	0	0	1	0	0	0	0
3	5	0	0	10	0	0	0	0	0	0	0	0	0	0
0	0	0	0	5	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	52	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	5	7	0
0	6	0	0	1	0	0	0	0	0	0	0	0	0	0
0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	10
0	0	0	0	6	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	17	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	2	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	94	0
0	0	0	0	0	0	0	0	0	0	2	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0	0	9	0
0	0	0	0	7	0	0	0	0	0	0	0	0	20	0
0	0	0	0	19	0	0	0	0	0	0	0	0	48	0
0	0	0	0	0	1	0	0	0	1	0	0	0	0	0
0	13	0	0	1	0	8	0	0	0	0	0	0	5	0
0	0	0	0	11	0	1	18	0	0	0	0	0	0	0
2	0	0	0	13	0	0	0	0	1	0	0	0	0	0
0	4	1	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	7	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	5	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	69	0	0	0	0	0	1	0	0	0	0
0	0	0	0	4	0	0	0	0	0	1	0	0	0	0
0	0	0	0	8	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	1	0	0	0	0
0	0	0	0	4	0	0	0	0	0	0	0	0	0	0
0	18	0	0	0	0	0	0	0	0	0	0	0	0	0
0	13	3	0	1	0	0	0	0	0	1	0	0	0	0
0	3	0	0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0

24.1	**24.2**	**24.4**	**24.7**	**25.7**	**26.1**	**26.2**	**26.4**	**26.6**	**26.7**	**27.1**	**27.2**	**27.7**	**28.1**	**28.2**
0	30	0	82	0	0	0	0	0	0	0	0	0	1	23
0	37	18	59	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	11	0	0	0	0	0	0	0
0	0	0	0	0	0	0	30	0	32	0	13	5	46	24
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	36	0	4	0	0	0	0	0
0	0	0	0	0	0	0	188	0	105	0	0	0	8	7
0	0	0	0	0	0	0	0	0	8	0	0	0	0	0
0	0	0	0	0	0	0	88	89	35	2	7	82	40	0
33	110	0	110	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	173	0	118	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	124	42	30	13
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	72	0	13	2	31	120	0	0
0	18	0	0	0	0	0	249	0	36	0	0	0	0	0
0	8	0	3	0	0	0	0	0	0	0	0	0	9	0
0	0	0	0	0	0	0	0	0	0	0	0	0	18	16
17	37	0	303	0	69	0	25	0	71	0	0	0	0	0
0	0	0	2	0	0	0	21	0	34	0	0	0	0	0
0	0	0	0	0	146	0	47	0	161	0	0	0	0	0
0	0	0	0	0	0	0	7	9	6	0	0	0	0	0
0	0	0	138	0	0	0	0	0	0	0	0	0	7	9
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	10	0	46	0	0	0	0	0	0	0	0	0	0	0
0	29	0	162	0	0	0	0	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	10	4
0	2	0	14	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	138	0	6	0	0	0	0	0
0	0	0	6	0	0	0	113	0	15	0	0	0	14	4
0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	6	0	0	0	0	0	0	0	0	0	0	0
0	1	0	5	0	0	0	0	0	0	0	0	0	5	14
0	4	0	2	1	0	0	0	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0	0	22	22
0	4	0	3	0	0	0	0	0	0	0	0	0	0	0
0	0	0	4	0	0	0	55	0	247	0	0	0	16	12
1	3	0	8	0	0	0	0	0	4	0	0	0	0	0
0	8	0	46	0	0	0	0	0	0	0	0	0	12	11
0	0	0	1	0	0	0	0	0	0	0	0	0	14	8

28.3	29.7	30.6	30.7	31.2	32.7	33.6	33.7	34.1	34.2	34.6	34.7	35.2	35.6	35.7
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	5	0	0	0	3	0	0	0
0	0	0	0	0	0	0	0	0	0	0	23	0	0	65
0	2	0	0	0	0	0	0	0	0	0	5	0	0	203
0	2	0	0	0	0	0	0	0	0	0	0	0	0	196
0	0	0	0	0	0	0	0	0	0	1	0	0	0	35
0	2	0	0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	18	0	0	16
2	2	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	6	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	16	64	0	196	0	28	0
0	2	0	0	0	0	0	0	0	0	0	8	0	0	2
0	0	10	5	0	0	0	0	0	0	0	0	3	0	1
0	0	0	0	0	0	0	0	0	0	0	3	0	1	5
0	0	0	0	0	0	0	0	0	0	0	7	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	289
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	25	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	11	0	0	0	0	0	60	0	0	18
0	0	0	0	0	0	0	0	0	0	0	14	0	0	0
0	0	0	0	0	0	0	0	0	0	0	14	0	0	0
0	0	0	0	0	0	0	0	0	0	0	30	0	0	0
0	0	0	0	0	0	0	0	0	0	0	2	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	4	0	14	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	24	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
0	3	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	3	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	9
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	2	0	0	0	0	0	0	0	0	0	0	0	0	0

36.2	36.7	37.7	38.1	38.2	39.1	39.2	39.4	39.7	40.2	40.6	40.7	41.2	41.7	42.2
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	3	0	0	0	0	0
0	0	0	0	0	10	0	0	56	0	0	3	0	0	0
0	0	0	0	0	0	0	0	71	0	0	10	0	0	0
0	0	0	0	0	0	0	0	81	0	0	40	0	0	0
0	0	0	0	0	0	0	0	89	2	0	0	0	0	0
0	0	0	0	0	0	0	0	33	3	0	0	0	9	0
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	161	8	0	0	0	0	0
0	0	0	0	0	0	0	0	23	7	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	4	0	0	0
0	0	0	0	0	0	0	0	36	0	0	1	0	0	0
0	16	0	0	0	0	0	0	14	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
0	0	0	0	0	0	0	0	40	1	0	2	0	0	0
0	0	0	0	0	0	0	0	91	0	0	0	0	0	0
0	0	0	0	0	0	0	0	24	0	0	0	0	0	0
0	5	0	0	0	0	0	0	0	0	0	3	0	0	0
0	0	0	0	0	0	0	0	65	0	0	11	0	0	0
0	6	0	0	0	0	0	0	3	0	0	22	0	2	0
0	0	0	0	0	0	0	0	18	0	0	0	0	0	0
0	0	0	0	0	0	0	0	12	9	0	21	0	1	0
0	13	0	0	0	0	0	0	26	0	0	6	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
0	12	0	0	0	0	0	0	0	0	0	44	0	0	0
0	0	0	0	0	0	0	0	0	0	0	5	0	1	0
0	0	13	0	0	0	0	0	3	0	0	0	0	0	0
0	0	0	0	0	0	0	0	15	0	0	0	0	0	0
0	0	0	0	0	0	0	0	15	0	0	0	0	0	0
0	0	0	0	0	0	0	0	11	0	1	4	0	3	0
0	2	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	2	0	0	0
57	0	0	0	0	0	1	1	114	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	67	0	344	55	0	311	0	1	0
0	0	0	0	0	0	0	0	20	46	0	261	0	0	0
0	0	0	0	0	0	0	0	9	0	0	165	0	5	1
0	27	0	0	9	0	0	0	0	65	0	193	0	0	0
0	20	0	0	9	0	0	0	6	0	0	24	0	6	0
0	0	0	2	3	0	0	0	111	0	0	224	0	1	0
0	0	0	0	20	0	1	0	8	0	0	0	1	0	0
462	0	0	0	4	0	0	0	0	59	0	503	0	0	0
0	0	0	1	0	0	1	0	1	0	0	121	0	0	0
38	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	46	0	236	0	0	0

42.7	**43.7**	**44.2**	**44.7**	**45.7**	**46.1**	**46.2**	**46.4**	**46.7**	**47.1**	**47.2**	**47.4**	**47.7**	**48.7**	**49.1**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	39	0	19	0	0
0	0	0	0	0	0	8	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	19	0	32	0	0
0	0	0	0	0	0	0	0	93	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	68	0	0	0	52	0	13	9	0
0	0	0	2	0	2	0	0	16	0	0	0	0	0	0
0	0	0	0	0	42	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	9	0	0	0	0	0	0
0	0	0	0	0	0	202	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	32	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	10	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	80	0	0
0	0	0	0	7	0	0	0	0	0	0	0	22	0	0
0	0	0	0	14	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	8	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	299	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	26	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	37	0	0	0	0	0	0	0	0	0	0	28	0	20
0	0	0	0	0	0	197	0	0	0	0	0	0	0	0
0	0	0	0	0	0	144	0	162	0	1	0	1	0	0
2	0	0	0	0	0	28	0	18	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	2	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	8	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

49.2	**49.7**	**50.7**	**51.2**	**51.7**	**52.2**	**52.6**	**52.7**	**53.7**	**54.7**	**55.1**	**55.2**	**55.7**	**56.2**	**56.6**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	17	26	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	4	19	18	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	9	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	3	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	6	0	0	0	0	0	0	0	0	0	0	0	0	0
0	30	0	0	0	0	0	0	0	0	0	0	0	0	0
0	16	0	0	0	0	0	0	0	0	0	0	0	0	0
0	7	0	0	0	0	0	0	0	0	0	0	0	0	3
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	11	0	0	0	0	0	0	0	0	0	0	0	0	0
0	11	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	13	0	0	0	0	0	0	0	0	0	0	0	0	0
0	13	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	10	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	4	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	27	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

56.7	**57.2**	**57.6**	**57.7**	**58.2**	**58.6**	**58.7**	**59.6**	**60.2**	**60.3**	**60.7**	**61.2**	**61.4**	**62.1**	**62.7**
0	0	18	0	0	0	50	0	0	15	70	0	0	1	0
2	0	0	0	0	0	43	0	0	0	50	0	0	0	2
0	0	0	1	0	0	0	0	0	0	114	0	0	0	0
1	38	0	20	0	0	0	0	21	0	53	0	0	0	2
1	80	0	0	74	0	0	0	0	0	5	0	0	0	2
1	11	0	0	0	0	0	0	0	0	40	0	0	0	2
2	0	0	0	0	20	46	0	0	0	23	0	0	0	2
0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
1	0	0	0	0	0	3	0	0	0	8	0	0	0	4
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	54	0	0	0	0	0	0	0	0	5	0	0	0	0
1	0	0	0	0	0	0	0	0	0	7	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	61	0	0	0	0	0	0	0	0	17	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	32	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	7	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	25	0	0	75	0	0	0	3	0	0	0	2
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	66	0	0	0	2
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	46	0	0	0	0
1	0	0	12	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	6	0	0	0	0
1	0	0	0	0	0	0	0	0	0	54	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	3	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
1	0	0	0	0	0	0	0	0	0	41	0	0	0	2
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	21	0	0	0	5
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	9	0	0	0	0
4	0	0	0	0	0	0	0	0	0	60	0	0	0	0
5	0	0	39	0	0	0	0	0	0	156	0	0	0	0
2	0	0	0	0	0	0	0	20	0	0	0	0	0	0
5	67	0	0	0	0	0	0	0	0	0	7	0	0	0
1	0	0	0	0	0	0	4	8	0	0	0	0	0	3
3	0	0	30	0	0	19	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	60	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	62	0	0	0	2
0	0	0	0	0	0	0	0	0	0	25	0	0	0	0

63.1	**63.2**	**63.4**	**63.7**	**64.6**	**65.1**	**65.3**	**65.7**	**66.2**	**67.7**	**68.1**	**68.7**	**69.2**	**70.1**	**70.2**
0	54	0	5	0	0	0	0	0	0	0	0	0	24	0
0	0	0	117	0	0	0	0	0	2	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	51	0
0	0	0	20	0	0	0	0	0	0	0	0	0	10	0
50	7	0	0	0	0	0	0	0	0	0	0	0	39	0
0	41	0	70	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	7	0	0	0	0	0	0	0	0	0	43	0
0	0	0	4	0	5	0	0	0	0	0	0	0	37	0
0	40	12	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	15	0	0	0	0	0	0	0	0	0	0	0
0	45	0	5	1	0	0	0	0	0	0	0	0	0	10
0	0	0	10	0	0	0	0	0	0	0	0	0	0	74
0	11	0	86	0	0	0	5	0	0	0	0	0	0	0
0	0	0	83	0	0	0	0	0	0	0	0	0	0	50
0	0	0	116	0	0	0	0	0	0	0	0	0	0	31
0	0	0	48	0	0	0	0	0	0	0	0	0	0	50
0	53	0	32	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	15	0	0
0	96	0	5	0	0	0	0	0	2	0	0	16	0	0
8	22	0	5	0	0	0	0	0	0	0	0	15	0	0
0	71	0	39	0	0	0	0	0	2	0	0	27	0	0
0	16	0	12	0	0	0	0	0	0	0	0	7	0	0
0	16	33	137	0	0	0	0	0	0	0	0	18	0	0
0	29	0	1	0	0	0	0	0	0	0	0	5	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	14	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	6	0	0	0	0	0	0
0	44	0	11	0	0	0	0	0	0	0	0	0	0	0
0	10	0	5	0	0	0	0	0	2	0	0	0	0	0
0	0	0	0	0	0	0	0	0	2	0	0	0	0	0
0	0	0	6	0	0	0	0	0	0	0	0	0	0	0
0	11	0	32	0	0	0	0	0	0	0	0	0	0	0
0	8	0	12	0	0	0	0	0	2	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	10	0	0	0	0	0	0	0	0	0	0	0
9	0	0	33	0	0	0	0	0	0	0	0	0	0	0
2	0	0	24	0	0	0	0	0	0	0	0	0	0	0
0	0	0	11	0	0	2	0	0	0	2	0	0	0	0
0	9	0	0	0	0	0	0	0	0	0	0	0	0	0
1	23	0	22	0	0	0	0	0	0	0	1	0	0	0
0	0	0	26	0	0	0	0	0	0	0	0	0	0	0
0	6	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	30	0	0	0	0	0	0	0	0	0	0	0
0	11	0	22	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	61	0	0	0	0	0	0	2	0	0	0	0

70.4	**70.7**	**71.7**	**72.7**	**72.2**	**73.4**	**73.7**	**74.7**	**75.7**	**76.2**	**77.7**	**78.2**	**79.7**	**80.6**	**80.7**
33	0	9	0	0	12	0	0	0	0	0	1	0	0	0
10	0	14	0	0	0	0	0	0	0	0	0	0	0	0
0	0	16	0	0	11	0	0	0	0	0	0	0	0	0
24	0	18	0	2	52	0	0	0	0	0	0	0	0	0
27	0	15	0	0	56	0	0	0	22	0	0	0	0	0
0	0	10	0	0	0	20	0	0	0	0	0	0	0	0
76	0	9	0	0	0	0	0	0	0	0	0	0	0	0
32	27	6	0	0	0	0	0	0	0	0	4	0	0	0
43	0	10	0	0	53	0	0	0	0	0	0	0	0	0
0	0	7	0	0	0	0	0	0	0	0	0	0	0	0
0	0	3	7	0	0	0	0	0	0	0	0	1	0	0
0	0	6	0	0	0	0	0	0	0	0	0	0	0	0
0	0	8	0	0	36	0	0	0	0	0	0	0	0	0
27	0	7	0	0	0	0	0	0	0	0	0	0	0	0
0	0	4	0	0	0	0	0	0	0	0	30	0	0	0
0	0	0	0	0	0	0	0	0	0	0	137	0	0	0
37	0	11	0	0	53	0	16	0	0	0	72	0	0	0
39	13	6	0	0	0	0	0	0	0	0	0	0	0	0
0	17	5	0	0	0	0	0	0	0	0	0	0	0	0
47	5	4	0	0	32	0	0	0	0	0	39	0	0	0
0	0	4	0	0	45	0	0	0	0	0	40	0	0	0
54	0	3	0	0	119	0	0	0	0	0	0	0	0	0
0	35	2	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	8	0	0	0	0	0	0	0	0	0	0	0	0
28	0	8	0	0	0	0	0	0	0	0	0	0	0	0
0	0	4	0	0	51	0	0	0	0	0	0	0	19	118
0	0	3	0	0	0	0	0	0	0	6	0	0	0	0
0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
0	0	2	0	0	23	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	7	3	39	0	0	0	0	0	0	0	0	0	0	0
23	16	7	8	0	45	0	0	0	0	0	0	0	0	0
0	0	5	0	0	0	0	0	0	0	0	0	0	0	0
0	18	6	0	0	12	0	0	0	0	0	0	0	0	0
0	0	4	0	0	7	0	0	0	0	0	0	0	0	0
0	0	3	0	0	0	0	0	0	0	0	0	0	0	0
16	0	4	0	0	21	0	0	0	0	0	0	0	0	0
0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
0	0	3	19	0	60	0	0	0	0	0	0	0	0	0
56	0	3	0	0	31	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	57	0	0	0	0	0	0
0	0	3	0	0	0	0	0	41	0	0	0	0	0	0
0	0	4	0	0	28	0	0	0	0	0	0	0	0	0
29	0	4	0	0	0	0	0	0	0	0	0	0	0	0
0	0	3	0	0	10	0	0	0	0	0	0	0	0	0
28	0	8	0	0	38	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0

81.7	**82.2**	**82.7**	**83.7**	**84.7**	**85.6**	**85.7**	**86.7**	**87.6**	**87.7**	**88.1**	**88.2**	**88.3**	**88.4**	**88.6**
0	0	1	0	0	0	0	0	0	1	0	14	0	10	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	28	0
0	0	1	0	0	2	0	0	0	0	0	0	0	0	0
0	0	4	0	0	0	0	0	1	0	0	0	0	0	0
0	0	3	0	0	0	0	0	0	0	0	0	0	0	0
0	0	3	0	0	0	0	0	0	0	0	0	0	49	0
0	0	3	0	0	0	0	0	0	0	0	0	0	0	0
0	0	3	0	0	0	0	0	0	0	0	0	0	52	0
0	0	2	4	0	0	1	0	0	1	0	0	12	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	38	0	40	0
0	0	0	0	0	0	2	0	0	0	0	3	0	23	0
0	0	6	0	0	2	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	45	0	39	0
0	0	3	0	0	0	0	0	0	0	0	19	0	0	0
0	0	1	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	29	0	50	0
0	0	1	4	0	0	0	0	0	0	0	36	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
0	0	13	0	0	0	3	0	0	0	0	30	0	0	0
0	0	0	0	0	0	0	0	0	0	0	30	0	0	0
0	0	6	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	16	16	0	0
0	0	1	0	0	0	0	0	0	0	17	22	0	45	0
0	0	4	0	0	0	0	0	0	0	3	38	0	60	0
1	0	1	0	0	0	0	0	0	0	0	27	0	0	0
0	0	6	0	0	0	0	0	0	0	12	47	0	0	0
0	0	5	0	0	0	0	0	0	0	0	0	0	18	0
0	0	0	0	0	0	0	0	0	0	0	17	0	45	0
0	0	0	0	0	0	0	0	0	0	0	13	1	0	0
0	2	1	0	0	0	1	0	0	0	0	12	0	0	0
0	0	3	5	0	1	0	0	0	0	0	6	0	30	0
0	0	1	4	0	0	0	0	0	0	0	22	0	28	0
0	0	4	0	0	0	0	0	0	0	0	0	0	0	16
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	43	0
0	0	3	0	0	0	2	0	0	0	0	2	0	0	0
0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
0	0	2	0	3	0	0	14	0	0	0	0	0	0	0
0	0	4	0	0	0	0	0	0	0	0	0	0	46	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	4	0	0	0	0	0	0	22	28	0	2	0
0	0	0	0	1	1	3	0	0	0	0	18	0	0	0
0	0	1	0	0	0	0	0	0	0	0	10	0	0	0
0	0	2	4	0	0	0	0	0	0	0	16	0	0	0
0	0	0	4	1	0	0	0	0	0	0	0	0	0	0
0	0	1	1	6	0	0	0	0	0	0	11	0	26	0

88.7	**89.2**	**90.1**	**90.2**	**91.1**	**91.2**	**91.3**	**91.4**	**91.7**	**92.2**	**92.5**	**92.7**	**93.5**	**93.6**	**94.6**
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	54	0	0	0	0	0	0	0	0	0	0	0
0	0	0	99	0	0	0	0	0	0	0	0	0	0	0
0	0	0	109	0	0	0	0	0	0	0	0	0	0	0
0	2	0	72	0	0	0	0	0	0	0	0	0	0	0
0	34	0	77	0	0	0	0	0	0	0	0	0	0	0
12	0	0	24	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	30	0	0	0	0	0	0	0	0	2	0
15	0	0	18	0	0	0	0	0	0	0	0	0	0	0
22	0	0	2	0	0	0	0	4	0	0	0	0	0	0
0	0	0	54	0	0	0	0	0	0	0	0	0	0	0
76	0	0	60	32	0	0	0	0	0	0	0	0	0	0
12	0	0	66	35	0	0	0	4	0	0	0	0	0	0
63	0	0	57	0	0	0	0	0	0	0	0	0	0	0
61	0	0	67	0	22	0	0	16	0	0	0	0	0	0
52	0	0	100	0	0	0	0	7	0	0	1	0	0	0
75	0	0	74	0	0	0	0	33	0	0	0	0	0	0
89	0	1	125	22	0	0	0	0	17	15	0	0	0	0
28	0	0	94	46	0	0	0	0	0	0	0	0	0	0
1	0	0	114	0	0	0	0	0	0	0	0	0	0	0
21	0	0	100	0	0	0	0	32	0	0	0	0	0	0
6	0	1	164	0	0	0	0	0	0	0	0	0	0	0
0	0	0	165	0	0	0	0	0	0	0	0	0	0	0
24	0	0	100	0	0	0	0	0	0	0	0	0	0	0
27	0	0	141	0	0	0	0	0	0	0	0	0	0	0
29	0	0	84	0	0	0	0	0	0	0	0	0	0	0
36	0	0	79	0	0	0	0	0	0	0	0	0	0	0
43	0	0	108	0	0	0	0	0	0	0	0	0	0	0
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28	0	0	27	0	3	0	0	24	0	0	0	0	0	0
57	0	0	6	0	0	0	0	0	0	0	0	0	0	0
81	0	0	23	0	0	0	0	22	0	0	0	0	0	0
59	0	0	54	0	0	0	0	0	0	0	0	0	0	0
20	0	0	89	0	0	0	0	0	0	0	0	0	0	0
32	0	0	67	0	0	0	0	0	0	0	0	0	0	0
34	0	0	20	0	0	0	0	0	3	0	0	0	0	0
11	0	0	12	0	0	0	0	6	0	0	0	0	0	0
71	0	0	27	0	0	0	0	0	0	0	0	0	0	0
12	0	0	10	0	0	5	4	0	0	0	0	1	1	0
31	0	0	15	0	0	0	0	3	0	0	0	0	0	0
0	0	0	5	0	0	0	0	5	0	0	0	0	0	0
3	0	0	21	0	0	0	0	4	3	0	0	0	0	0

94.7	**95.7**	**96.2**	**97.2**	**97.7**	**98.7**	**99.7**	**100.6**	**101.7**	**102.3**	**102.4**	**103.7**	**104.4**	**105.7**
0	0	0	0	0	0	0	0	0	0	16	0	11	0
0	1	0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	5	9	0	56	0
0	0	1	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0	2	0	0	0
0	0	0	0	0	0	0	1	0	0	15	0	167	5
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	1	0	132	0
0	0	0	0	0	0	0	0	0	0	26	0	326	0
0	0	0	0	0	0	0	0	0	0	0	0	37	0
0	0	0	0	0	3	0	0	0	0	0	0	122	0
0	0	0	0	0	3	0	0	0	0	0	0	12	0
0	0	0	0	0	0	0	0	0	0	0	0	3	0
0	0	0	0	0	0	0	0	0	0	2	0	218	0
0	0	0	0	0	0	0	0	0	0	0	6	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	44	0	0	0
0	0	0	0	18	0	0	0	0	0	0	0	129	0
0	0	0	0	0	0	0	0	0	0	2	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	57	0	144	0
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0	0	0	0	0	0	0	0	0	0	41	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	139	0
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0	0	0	0	0	0	0	0	0	0	1	0	62	0
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0	0	0	0	0	0	0	0	0	0	1	0	0	0
21	0	0	32	16	0	0	0	0	0	2	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	84	0
0	0	0	0	0	0	0	0	0	0	1	0	120	0
0	0	0	0	0	0	0	0	0	0	2	0	0	0
0	0	0	0	0	0	0	0	0	0	3	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	202	0
0	0	0	0	0	0	0	0	0	0	10	0	41	0
0	0	0	0	0	0	0	0	0	0	0	0	136	0
0	0	0	0	0	0	0	0	0	0	2	0	6	0
0	0	0	0	0	0	0	0	0	0	10	0	0	0
0	0	0	0	0	0	25	0	0	0	29	0	216	0
0	0	0	0	0	0	0	0	0	0	14	0	61	0
0	0	0	0	0	0	0	0	0	0	1	0	120	0
0	0	0	0	0	0	0	0	0	0	1	0	182	0
0	0	0	0	0	0	0	0	0	0	2	0	78	0
0	0	0	0	0	0	0	0	0	0	20	0	44	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	8	0	159	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0

106.2	**106.6**	**106.7**	**107.5**	**108.7**	**109.6**	**109.7**	**110.7**	**111.2**	**112.2**	**113.7**	**114.7**	**115.7**
172	0	129	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
58	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	2	2	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	2	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	3	0
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0	0	0	0	0	0	0	0	0	0	1	0	0
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0	0	0	0	0	0	0	0	0	0	1	0	0
53	0	0	0	0	0	0	28	0	0	0	0	0
53	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	8	0	0	0
0	0	0	0	63	0	0	0	0	0	0	0	0
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0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	2	0	0	0	0	0	0	0
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0	0	0	7	0	0	0	0	0	0	0	0	0
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0	0	0	0	6	0	0	0	0	0	0	0	0
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0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	2	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	31	0	0	0	0	0	0	0	0
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0	0	0	0	42	0	0	0	0	0	0	0	0
0	0	0	0	38	0	0	0	0	0	1	0	0
0	0	0	0	63	0	0	0	0	0	0	0	0
0	0	0	0	19	0	0	0	0	0	0	0	0

116.7	117.3	117.6	117.7	118.7	119.1	119.7	119.7	120.7	121.5	121.7	122.1	122.2
0	0	2	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	10	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
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2	0	0	0	0	0	0	1	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0
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2	0	0	0	0	0	0	0	0	0	0	0	23
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0	0	0	0	0	0	0	0	0	0	0	0	3
0	0	1	4	0	0	0	0	0	0	0	0	22
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	53	0	0	0	0	0	0	0
0	0	0	0	18	0	0	0	0	0	0	2	20
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
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0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	31	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	7	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	2	0	0	0	0	0	0	0	0	0	2	0
0	0	0	0	0	0	0	0	0	19	7	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
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0	0	0	0	0	0	0	0	0	0	0	0	0
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0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	4	0	0	0	0	0	0	0	0	0

122.7	123.7	124.3	124.6	124.7
0	8	0	0	0
0	8	0	0	0
0	2	0	0	0
0	6	0	0	0
60	13	0	0	0
19	8	0	0	0
0	4	0	0	0
0	0	0	0	0
0	4	0	0	0
18	6	0	0	0
0	0	0	0	0
0	2	1	0	0
0	10	0	0	0
0	7	0	0	0
0	6	0	0	0
0	4	0	0	0
40	13	0	0	0
5	9	0	0	0
0	4	0	0	0
0	10	0	0	0
0	5	0	0	0
0	7	0	0	0
0	7	0	0	0
0	6	1	0	0
0	17	0	0	0
0	7	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	2	0	0	0
0	1	0	0	0
0	10	0	0	0
0	2	0	0	0
0	0	0	0	0
0	1	0	1	0
0	0	0	0	0
0	5	0	0	0
0	1	0	0	0
0	1	0	0	0
0	0	0	0	0
0	0	0	0	0
0	3	0	0	0
0	20	0	0	0
0	14	0	0	0
0	2	0	0	1
0	0	0	0	0
0	9	0	0	0
0	8	0	0	0

APPENDIX E

Research Quad chart summarizing the background, research questions, methodology, results, conclusions and potential future works for this thesis…

Optimizing Forecasting Methods for Intermittent USTRANSCOM Railcar Demands

1st Lt James Park
Advisor: Dr. Jeffery D. Weir
Reader: Dr. Raymond R. Hill
Department of Operational Sciences (ENS)
Air Force Institute of Technology

Introduction

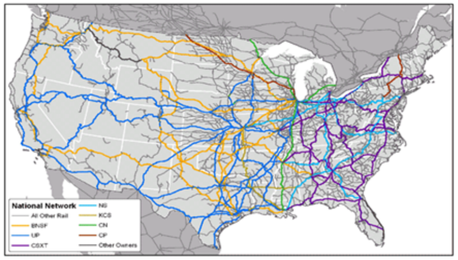
- US Military heavily relies on rail freight operations to meet its logistical needs during both peacetime and wartime efforts
- Irregular and intermittent nature of railcar demands create an extremely challenging task for forecasters
- Forecasts drive distribution and placement of railcar commodities resulting in critical costs and impacts

Problem Statement

USTRANSCOM* requires an improved process for determining accurate timely forecasting strategies for intermittent demands and a system to better understand forecasting accuracy.

Research Questions

- Are there techniques to improve forecast accuracy for railcars?
- Are there more relevant and meaningful ways to measure forecast accuracy?
- Are there ways to automate the system?



AIR FORCE INSTITUTE OF TECHNOLOGY

Methodology

Step 1: Data Gathering and Organization

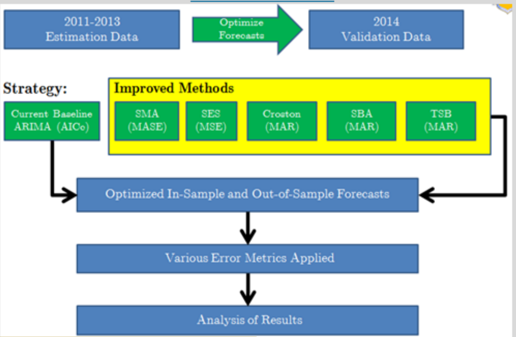
USTRANSCOM Surface Deployment and Distribution Command's (SDDC) rail freight movement records

Monthly train demands by origin (Jan 2011 – Dec 2014)

Further filtered and organized by rail commodity type

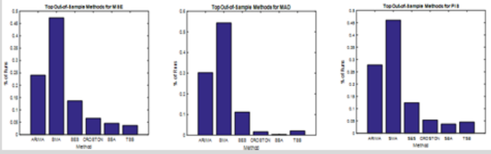
Useable data: 241 separate time series organized to track demand for a certain commodity at specific locations

Step 2: Optimize Forecasts Based On Specific Cost Functions



Results and Analysis

Initial Results



- Out-of-Sample: Percentage when each technique is the top option is shown for each metric
- In case of ties, wins are given to ARIMA as it is used as a baseline and research seeks improvements

Overall Rankings for Methods

Out of Sample Ordered			Equal				
		Average Rank					
MSE	SMA	2.398	🟩				
	SES	2.477	🟩				
	TSB	2.739					
	SBA	3.490		🟩			
	CROSTON	3.527		🟩	🟩		
	ARIMA	3.838			🟩		

Out of Sample Ordered			Equal				
		Average Rank					
MAD	SMA	2.021					
	SES	2.490					
	TSB	2.859					
	ARIMA	3.307					
	SBA	3.859	🟩				
	CROSTON	3.871	🟩				

Out of Sample Ordered			Equal				
		Average Rank					
PIS	SMA	2.456	🟩				
	SES	2.535	🟩				
	TSB	2.768					
	ARIMA	3.527		🟩			
	SBA	3.573		🟩			
	CROSTON	3.618		🟩			

- Out-of-Sample: Methods are ranked and averaged across the board for each error metric
- Green lines indicate statistical equivalence $\alpha=0.05$

Hit Rate Analysis

Based on the best forecasting method from the In-Sample dataset, what percentage of the time is that method also the best method for the Out-of-Sample dataset?

Strategy Comparison	Hit Percentage		
	MSE	MAD	PIS
Current ARIMA (Baseline)	16.60%	28.63%	16.60%
Improved Methods	24.90%	52.28%	42.32%

Strategy Comparison	Hit Percentage
	Combined Scaled Error
Current ARIMA (Baseline)	28.63%
Improved Methods	53.53%

Conclusion/Recommendations

- For railcar demands, simpler is better
  - Optimized SMA and SES performed very well compared to more complex techniques
  - Hit Rate Analysis suggests MAD to be most valuable in optimizing and determining future forecasts
- Croston's Method should only be used for research purposes and would be disadvantageous in practical settings

Future Research

- Adding cost dimensions to forecasts with expenditures and savings
  - Tangible and intangible costs
- Classification and categorization strategies for lumpy time series data
- Intermixing and combining usage of various railcars for common missions

Sponsor:
USTRANSCOM/JDPAC

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14. ABSTRACT

The United States military heavily relies on rail freight operations to meet many of its logistical needs during both peacetime and wartime efforts. As the head organization responsible for managing and overseeing all modes of military transportation, United States Transportation Command depends on timely accurate railcar demand forecasts to drive critical decisions on distribution and placement of railcar assets. However, the intermittent nature of railcar demands based on location and commodity make it a challenging task for forecasters. Furthermore, these "lumpy" demands often come without any obvious trends or seasonality. This study explores the utility of both traditional forecasting methods and newer techniques designed specifically for handling intermittent demands. All forecasting parameters for each method are optimized based on specific cost functions. Accuracy metrics are then applied to all forecasts for analysis. The results indicate that for the Department of Defense's railcar demands, optimizing basic forecasting methods such as Simple Moving Averages and Simple Exponential Smoothing outperform more popular methods for sparse demands such as Croston's method and its variants. Despite its theoretical superiority, applying Croston's method to railcar demands was found questionable and consistently produced poor forecasts compared to other methods. Analysis provides valuable insight in future strategies for forecasting intermittent demands.

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